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3Decentralized Robust FDI for Inertia, Damping, and Turbine-Governor Time Constants in Interconnected Grids via Combined H_∞/H_2 -Pole Placement and Sliding Mode Techniques

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Abstract

The growing integration of renewable sources and the expansion of interconnected grids have heightened power systems' susceptibility to parametric uncertainties. These include mechanical deterioration, turbine blade damage, reduced system inertia, and deliberate cyber-physical intrusions impacting turbine-governor assemblies, synchronous generators, and interconnecting transmission paths. Left unaddressed, such anomalies can seriously impair frequency and voltage stability, potentially escalating into widespread grid disturbances. While standard observer techniques successfully flag the presence of irregularities, they typically fall short in determining which specific parameter has deviated. The present work introduces a comprehensive and resilient Fault Detection and Isolation (FDI) methodology that can both estimate and accurately localize alterations in several fundamental dynamic parameters: turbine time constant (T_t), governor time constant (T_g), moment of inertia (H), load damping coefficient (D), and inter-area synchronizing coefficients (T_{ij}). The approach combines a mixed H_∞/H_2 observer augmented with regional pole-placement constraints—ensuring strong rejection of external disturbances and rapid residual generation—with a subsequent adaptive sliding-mode estimation stage tailored for precise parameter identification and fault classification. Thanks to this cascaded structure, the scheme reliably separates genuine parametric faults from measurement noise and distinguishes among different classes of parameter drift. Extensive simulations on a representative multi-area load frequency control (LFC) benchmark demonstrate the method's high estimation accuracy and strong robustness across various fault magnitudes and types. In marked contrast to most existing FDI strategies, which are limited to detection, the proposed framework additionally pinpoints the physical or cyber origin of each fault. This added diagnostic capability supplies operators with concrete, decision-ready information and substantially bolsters the fault tolerance and overall dependability of large-scale modern power networks.

Keywords Interconnected power grids, H_∞/H_2 observer with pole placement, Adaptive sliding mode parameter estimation, Fault detection and isolation (FDI), Turbine–governor time constant estimation, Inertia constant estimation

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Introduction

Today's large-scale interconnected power systems are intricate networks increasingly prone to internal abnormalities that threaten overall grid integrity. Deviations in several core model parameters—namely, turbine–governor time constants, generator inertia constants (H), load-damping coefficients (D), and tie-line synchronizing coefficients (T_{ij})—serve as

primary early-warning signals of emerging issues. Without continuous surveillance and swift corrective measures, these shifts can provoke deteriorated primary frequency control, intensified sub-synchronous oscillations, propagating instability cascades, prolonged frequency excursions, and heightened probability of voltage instability or collapse during post-disturbance recovery [1].

Degradation of governor–turbine time constants commonly arises from physical wear mechanisms such as blade loss, surface erosion [2], progressive aging and mechanical fatigue, actuator wear, valve sticking, increased deadband that delays control action [3], alterations in hydraulic subsystems [4, 5], and fluctuating ambient or loading conditions.

Parallel to governor–turbine parameter drift, the aggregated system inertia (H) has been steadily declining as inverter-interfaced generation displaces conventional synchronous machines [6]. Further reductions in effective inertia may stem from mechanical wear processes, including rotor degradation or bearing damage [6, 7]. Load damping (D) characteristics are likewise vulnerable to variations in the damping coefficient itself [8] or to malfunctions within excitation control loops [9]. Meanwhile, unexpected changes in tie-line synchronizing coefficients (T_{ij}) frequently indicate hardware issues (e.g., line conductor faults, sensor errors) [10], malicious cyber intrusions [11], or communication breakdowns that indirectly modify apparent line reactance [12] and thereby endanger angular and voltage stability across regions [13].

The preceding points underscore the strategic value of real-time parameter tracking, which enables proactive grid management. Reliable governor time-constant estimation, for instance, is indispensable for anticipating and suppressing sub-synchronous resonance (SSR) phenomena. Timely detection of declining synchronizing coefficients permits operators to initiate preventive countermeasures—such as re-dispatching active power or retuning excitation systems—to avert loss of synchronism and prevent uncontrolled islanding [13, 14]. Likewise, ongoing inertia estimation equips control centers to identify emerging low-inertia scenarios and deploy appropriate fast-acting frequency support resources or adjust operating reserves accordingly [7].

Observer-based techniques have long played a central role in power system fault diagnosis. Sliding mode observers (SMOs), in particular, exhibit robust performance in the presence of actuator malfunctions, bounded-magnitude load disturbances [15], model parameter mismatches [16], and sensor failures [10]. Liu *et al.* [11] describe a unified fault-estimation and fault-tolerant control architecture that preserves closed-loop stability despite simultaneous sensor faults and deception-type cyberattacks. Another study develops an active, fault-tolerant load-frequency regulation strategy based on a proportional–derivative sliding-mode observer that continuously reconstructs both fault signals and system states. In that framework, a Lyapunov–Krasovskii-based sufficient condition is derived to guarantee asymptotic stability of the controlled multi-area network.

In Mahmud *et al.* [17], feedback linearization is applied to achieve exact linearization of the power system model, enabling the design of a nonlinear observer. For the resulting linearized system, an excitation control strategy is formulated, and the observer's estimated states serve directly as controller inputs, eliminating the need to formulate the control law using all available measurements.

Tran and Trinh [18] introduce a distributed functional observer-based fault detection (FD) strategy tailored for interconnected systems subject to time delays and unknown inputs. Independent residual generators are deployed at each subsystem to identify actuator faults. The choice between a reduced-order distributed functional observer or a decentralized counterpart depends on the degree of coupling among subsystems.

Ferdowsi and Jagannathan [19], a decentralized scheme for fault detection and accommodation for nonlinear continuous-time interconnected systems, relying solely on local subsystem states. Fault presence is identified through a locally computed residual comparing measured and estimated states, while an online approximator reconstructs fault dynamics. Following detection, a separate online approximator adjusts the control input at each subsystem to compensate for the fault and limit its propagation across the network.

Hamdi *et al.* [20] developed a recursive distributed algorithm for parameter estimation in large-scale systems composed of multiple interconnected subsystems. The method minimizes prediction errors, with convergence rigorously analyzed via Lyapunov techniques.

In Krishnan and Iyengar [21], fault detection is achieved using a minimal set of phasor measurement units (PMUs), with the optimal placement determined by the particle swarm optimization (PSO) algorithm. Boem *et al.* [22] present an innovative distributed fault-detection technique for large-scale linear systems composed of interconnected subsystems. It employs a partition-oriented distributed Luenberger-style estimator that accounts for inter-subsystem dynamic interactions and derives a variance bound on the residual. Local fault-detection thresholds are then set based on uncertainties propagated from estimates in adjacent subsystems.

Kazerooni *et al.* [23] utilize robust adaptive observers to concurrently detect faults and estimate both states and faults within individual subsystems. Asymptotic stability guarantees are provided through sufficient conditions formulated as matrix inequalities, underpinned by a Lyapunov–Krasovskii functional.

In Shams and Rahmani [24], a novel distributed observer is proposed for simultaneous fault and state estimation in load frequency control (LFC) of multi-area interconnected power systems incorporating time delays. The observer design conditions are cast as optimization tasks solvable via Linear Matrix Inequality (LMI) methods. Wiltshire *et al.* [25] leverage Kalman filtering to identify modal variations in extensive, interconnected power grids, establishing short-term alert mechanisms grounded in the statistical analysis of the Kalman innovation's power spectral density.

Glickman *et al.* [26] enhance conventional Fourier-based techniques for estimating damping factors. Pathak *et al.* [27] describe a real-time intelligent control approach for parameter estimation that dynamically tunes its own gain parameters.

In Genc and Caliskan [28], a method is outlined for detecting and isolating performance degradation in generating units within load-frequency control frameworks, employing an unknown-input observer that remains robust to fluctuations in load demand. Tirandaz *et al.* [29] examine actuator fault detection and isolation in large-scale, nonlinear, interconnected systems subject to modeling uncertainties and measurement noise. Maurer *et al.* [30] integrate Kalman filtering with wavelet transforms and random decrement techniques to estimate frequency and damping ratios.

In Othman and Amari [31], signal processing combined with wavelet analysis enables rapid fault detection in transmission lines, while an artificial neural network classifies the fault positions. Caliskan and Genc [32] implement a robust approach to sensor and actuator fault detection in interconnected power system load-frequency control using unknown-input observers. Zhang *et al.* [33] present a discriminant analysis technique for real-time fault detection and isolation utilizing PMU data.

In Liang *et al.* [34], a distributed fault detection and isolation strategy is proposed for large-scale power systems subject to energy-bounded disturbances, featuring local residual generators constructed using Luenberger observers. Li and Wu [35] describe a fault detection technique grounded in linear matrix inequality optimization and the Bounded Real Lemma, in which faults are confirmed by comparing residuals under healthy and faulty operating conditions. Alhelou *et al.* [36] explore a particle filter-driven decentralized method for dynamic state estimation in multi-machine interconnected power systems.

In Geetha *et al.* [37], a hierarchical parallel algorithm for dynamic estimation is introduced for large-scale interconnected power systems. It processes estimation locally within smaller subsystems before aggregating results to form a global state estimate. Kekatos and Giannakis [38] offer a comprehensive framework that unifies various distributed power system state estimation (PSSE) approaches and proposes a novel algorithm based on the alternating direction method of multipliers.

Liu and Lim [39] develop an algorithm for identifying parameter errors from real-time measurements by combining sensitivity-driven error detection with weighted least-squares (WLS) estimation. Lee *et al.* [40] adopt a model-independent technique that processes generator frequency measurements to locate faults and estimate their severity via logistic and linear regression models.

In Aluko *et al.* [41], a control strategy is presented that combines a robust unknown-input observer with an interval type-2 fuzzy logic controller to enable adaptive load-frequency control in interconnected power systems with substantial renewable energy integration. Haes Alhelou *et al.* [42] propose an entirely decentralized load-frequency control approach based on dynamic state estimation (DSE).

Yang *et al.* [43] introduce a data-driven technique for determining effective inertia across regions of power systems, based on eigenstructure analysis. The method derives clear mathematical links among inertia, eigenvalues, and eigenvectors based on the linearized system dynamics. Additionally, dynamic mode decomposition is applied to recover eigenvalues and eigenvectors straight from time-synchronized measurements, including those obtained via phasor measurement units (PMUs).

In recent years, machine learning techniques have become increasingly prominent in power system state estimation. Tian *et al.* [44] propose a neural network-based state estimation (NNSE) approach that improves computational speed, resilience to measurement noise, and system observability compared with conventional weighted least-squares (WLS) techniques. Moreover, Roy *et al.* [45] present a deep learning strategy employing a Long Short-Term Memory (LSTM) network for real-time fault detection and categorization in microgrids. To tackle the more demanding task of pinpointing fault locations (as opposed to mere classification), the authors combine LSTM with feed-forward neural networks (FFNN) and optimize via a back-propagation algorithm (BPA).

Bouchiba and Kaddouri [46] explore the use of deep learning and support vector machine methods for fault detection in power systems, focusing on the IEEE 14-bus test case. In Alhanaf *et al.* [47], three distinct deep learning architectures—CNN, LSTM, and a hybrid CNN–LSTM—are developed to perform line fault identification, fault type classification, and fault position estimation.

Padmaja and Sudha [48] describe an adaptive tuning mechanism for support vector machines (SVM) applied to load frequency control (LFC), aimed at maintaining frequency stability and tie-line power exchange in interconnected grids. The tuning process uses Monte Carlo sampling to account for parameter uncertainties.

Contemporary fault-diagnosis strategies have increasingly adopted neural-network-driven iterative learning frameworks. Examples include reinforcement-based iterative learning for fault estimation in nonlinear uncertain manipulator systems featuring time delays [49], neural-network compensator-enhanced robust iterative learning control for mobile robots subject to disturbances and parameter uncertainties [50], and neural-network-supported robust iterative learning fault estimation for general nonlinear uncertain systems [51]. Although these approaches excel at managing nonlinear behavior and uncertainties, they generally require large training datasets, entail substantial offline computational burden, and offer limited transparency into the physical meaning of generated residuals. Furthermore, extending such data-intensive methods to high-dimensional, real-time scenarios—such as those encountered in extensive, interconnected power grids—poses significant practical challenges.

By comparison, the current paper presents a fully model-based Fault Detection and Isolation (FDI) architecture specifically designed for interconnected power systems. Drawing on a combined H_∞ /pole-placement observer design, the proposed scheme eliminates any reliance on training data, ensures guaranteed robustness against bounded disturbances, and maintains strong physical interpretability of residuals directly tied to specific parameter shifts. In addition, the approach offers attractive computational efficiency, with offline LMI-based synthesis scaling as $O(n^{3.5})$ and online estimation requiring only $O(n^2)$ operations—rendering it suitable for real-time deployment even in systems comprising hundreds of states.

Emerging challenges

Contemporary power grids confront several critical dynamic issues, including:

- Rising integration of renewable energy sources results in reduced overall system inertia [6].
- Expanded dependence on communication infrastructures and advanced control layers, thereby exposing the grid to risks from deception, cyberattacks, and unexpected topology alterations [11, 12].
- More intricate inter-area oscillatory modes that are difficult to dampen owing to diverse, heterogeneous generation portfolios [14].

Consequently, effective fault detection strategies must extend beyond conventional estimation of sensor or actuator faults to explicitly estimate, isolate, and track variations in essential system parameters such as T_g , T_t , H , D , and T_{ij} . This capability supports proactive mitigation before small anomalies evolve into major instabilities.

Limitations of existing methods

Although observer-based approaches, including sliding mode observers (SMOs), perform robustly in identifying actuator faults, sensor failures, and deception-type attacks, they commonly presuppose that core system parameters (T_g , T_t , H , D , and T_{ij}) remain constant and precisely known. In real-world operation, however, these parameters are prone to gradual or abrupt changes caused by component aging, turbine blade damage or erosion, mechanical fatigue, network reconfiguration, or combined cyber-physical threats. Moreover, prevailing techniques frequently interpret dynamic deviations solely as actuator or sensor issues, without isolating the precise underlying parameter responsible. For instance, an SMO might flag an irregularity in overall behavior but fail to distinguish whether the source lies in governor malfunction or diminished inertia.

This limitation calls for more sophisticated estimation and isolation mechanisms that can capture temporal drift across distinct time constants and parameters. By formulating explicit disturbance matrices, the H_∞/H_2 pole-placement framework enables precise bounding of estimation errors. These refined state estimates then feed into a suite of sliding-mode estimators, enabling accurate estimation, fault isolation, and continuous monitoring of variables indicative of faults across diverse system components.

In this work, a thorough examination is conducted to connect individual system parameters to their corresponding fault mechanisms, emphasizing the need for ongoing parameter surveillance. A dedicated bank of estimators—one aligned with each key parameter—is constructed, facilitating the recognition and separation of unique fault “signatures.” This represents a significant advancement, as it enables simultaneous detection, isolation, and quantification of faults affecting turbines, governors, shafts, transmission corridors, and load-damping characteristics across interconnected power systems.

Scope of this paper

The present work develops an innovative Fault Detection and Isolation (FDI) framework with a primary emphasis on parameter estimation and precise isolation. Employing a unified H_∞/H_2 observer incorporating pole placement constraints, the proposed technique facilitates:

- Robust and accurate estimation of key parameters in turbine–governor systems, namely time constants (T_g , T_t), load damping coefficient (D), inertia constant (H), and tie-line synchronizing power coefficient (T_{ij}).
- Clear identification and isolation of the particular parameter subject to deviation, thereby supporting focused diagnostic analysis.

- Strong resilience against modeling inaccuracies, bounded exogenous disturbances, and unknown inputs.

Main contributions

The principal contributions of this research are outlined below:

1. **Robust FDI Framework:** An advanced fault detection and isolation structure designed to concurrently estimate and isolate deviations in T_g , T_t , H , D , and T_{ij} within interconnected power systems.
2. **H_∞/H_2 Pole Placement Observer:** An original observer formulation that ensures specified pole locations for accelerated fault detection, while effectively mitigating disturbance effects through a balanced H_∞/H_2 optimization.
3. **Interconnected System Validation:** Implementation and evaluation of the proposed method on a multi-area power system incorporating load frequency control (LFC) dynamics, with performance assessed across multiple fault conditions.

Integration with sensor fault and cyber-attack detection

This investigation assumes trustworthy sensor data and concentrates chiefly on isolating genuine physical parameter shifts in multi-area LFC configurations (e.g., T_g , T_t , H , D , and T_{ij}). In real-world applications, however, sensor malfunctions or cyber intrusions may undermine measurement reliability. Accordingly, the parametric FDI approach developed here is best viewed as complementary to sensor-oriented fault and attack detection techniques, such as the distributed networked estimation frameworks presented by Doostmohammadian *et al.* [52]. Those strategies handle sensor/output faults in expansive large-scale dynamical systems (LDS) through single-time-scale networked estimation, probabilistic thresholding of residuals, and q -redundant observer designs.

An effective defense-in-depth architecture would deploy the parameter-focused FDI scheme concurrently with sensor-centric methods: the latter safeguard the cyber domain by detecting and excluding tainted measurements, whereas the former scrutinize the physical domain to identify authentic alterations in system dynamics. This layered, synergistic methodology delivers thorough resilience, protecting both data trustworthiness and the integrity of essential physical assets.

Parameter Variations of Interconnected Power Systems

System stability and operational efficiency in interconnected power grids depend critically on parameters such as turbine and governor time constants, inter-area synchronizing power coefficients, equivalent inertia constants, and load damping coefficients. Deviations in these values—stemming from component failures, progressive wear, or external perturbations—can markedly impair performance, resulting in instability, inadequate frequency control, and potential cascading outages [53].

Precise estimation of these parameters, encompassing turbine and governor time constants, synchronizing power coefficients, inertia constants, and load damping coefficients, is indispensable for dependable grid management. Such deviations may result from equipment deterioration, sensor inaccuracies, faults, or structural network modifications. This section examines the mechanisms underlying these parameter changes and evaluates their effects on overall system behavior.

Turbine time constant (T_t) variation

The turbine time constant is expressed as follows:

$$T_t = \frac{\text{Change in mechanical power output}}{\text{Rate of governor valve opening}} \quad (1)$$

Where:

- T_t denotes the turbine time constant (typically measured in seconds),
- Mechanical power output represents the power produced by the turbine,
- The governor valve opening rate determines how quickly the turbine responds to load variations.

In mathematical terms, turbine dynamics are frequently approximated by the first-order equation:

$$\frac{\Delta P_m(s)}{\Delta P_v(s)} = \frac{1}{T_t s + 1} \quad (2)$$

Where:

- P_m stands for the mechanical power delivered by the turbine,
- P_v indicates the governor-controlled valve position,
- T_t is the turbine time constant.

Causes of T_t variation

Variations in T_t arise from a range of physical and operational influences:

- (1) Damage to turbine blades (including cracks and erosion), which modifies eigenmodes and torsional behavior [54-57];
- (2) Thermal stresses induced by nonuniform heating and cooling cycles;
- (3) Malfunctions in hydraulic or steam systems (such as leaks or valve failures);
- (4) Deterioration within the control system (e.g., actuator faults or increased mechanical friction);
- (5) Variations in steam quality for thermal generating units;
- (6) Hydraulic oscillations in hydroelectric units (arising from penstock dynamics or gate obstructions) [58].

Monitoring Importance:

Precise estimation of T_t holds significant value for:

- (1) Improving the accuracy of dynamic models used in stability analysis [59];
- (2) Detecting early signs of mechanical or control system wear;
- (3) Supporting effective emergency control actions under disturbance conditions;
- (4) Preserving rotor angle and frequency stability [59];

- (5) Mitigating subsynchronous resonance phenomena [60];
- (6) Facilitating optimal load distribution and enhanced power quality.

Taken together, these aspects highlight the central importance of T_t in ensuring grid reliability, designing effective protection systems, and suppressing undesirable oscillations.

Governor time constant (T_g) variation

The governor time constant, T_g , characterizes the speed of response of the governor control loop, which adjusts turbine valve position in reaction to frequency deviations across interconnected power networks [61].

The standard transfer function used to model governor dynamics is given by:

$$\frac{\Delta P_v(s)}{\Delta f(s)} = \frac{K_g}{T_g s + 1} \quad (3)$$

where:

- ΔP_v represents the change in valve position,
- Δf denotes the frequency deviation,
- K_g is the governor gain,
- T_g is the governor time constant.

Causes of T_g variation

1. Mechanical Degradation: Progressive wear in mechanical linkages, servomotors, and hydraulic actuators increases response latency. Over time, aging leads to changes in oil viscosity, further delaying governor action.
2. Maintenance Practices: Inadequate maintenance leads to sluggish component movement, whereas regular lubrication and timely replacement of worn parts help maintain an optimal T_g .
3. Faults & Malfunctions: Valve sticking, linkage fractures, sensor or actuator failures, and control logic errors all introduce additional delays in governor response.
4. Control Adjustments: Deliberate retuning of governor settings—such as gain or droop characteristics—directly modifies the system's dynamic time response.
5. Hydraulic/Pneumatic Issues: Leaks in pressure lines, air ingress, or fluid contamination degrade actuator performance and slow overall response.
6. Environmental Effects: Fluctuations in ambient temperature influence oil viscosity and the efficiency of pneumatic components.
7. Sensor Drift: Gradual inaccuracies in speed or pressure sensing impair the governor's ability to respond effectively over extended periods.

Impact on System Performance:

1. Sub-Synchronous Resonance (SSR): An excessively slow governor (elevated T_g) is unable to adequately damp torsional oscillations, increasing vulnerability to SSR instability [62-64].
2. Poor Frequency Control: Slower corrective action exacerbates frequency excursions following load or generation disturbances.
3. Overshoot & Instability: Delayed interventions can result in large frequency undershoots or out-of-step conditions across multiple areas.
4. Reduced Damping: Sluggish governor response diminishes the damping of inter-area electromechanical oscillations, compromising overall stability [64].

Synchronizing power coefficient (T_{ij}) variation

T_{ij} quantifies the strength of electrical coupling between two interconnected control areas. It is directly governed by tie-line impedance, bus voltage magnitudes, and the angular separation between the areas [14].

$$T_{ij} = \frac{V_i V_j}{X_{ij}} \cos(\delta_i - \delta_j) \quad (4)$$

Where:

- V_i, V_j = voltage magnitudes at buses i and j ,
- X_{ij} = reactance (impedance) of the interconnecting tie-line,
- δ_i, δ_j = rotor (phase) angles at buses i and j .

Causes of variation

- Line Outages: Disconnection of a key tie-line substantially lowers T_{ij} , thereby reducing the synchronizing torque between areas.
- Impedance Shifts: Accumulation of ice, contact with vegetation, or increased conductor sag can raise the effective line impedance.
- Voltage Instability: Insufficient reactive power support, leading to voltage sags or swings, diminishes T_{ij} .
- Topology Changes: Switching operations or breaker actions modify power flow routes and alter inter-area coupling strength.

Stability consequences

- Reduced Synchronization: A decline in T_{ij} weakens the synchronizing restoring torque that keeps areas in step.
- Cascading Risks: Crossing critical thresholds can precipitate uncontrolled separation of areas [23].
- Oscillation Risks: Lower tie-line coupling reduces damping of inter-area oscillatory modes.
- Transfer Capacity Limits: Operators must impose generation redispatch and activate special protection measures to maintain secure operation.

Monitoring imperatives

- Preventive Diagnostics: Real-time detection of declining coupling enables early identification of faults or outages.
- Corrective Action: Facilitates timely interventions—such as generation rescheduling or excitation retuning—to prevent:
 - Rotor angle instability
 - Loss of synchronism
 - System islanding or fragmentation [13, 14, 61].

Inertia constant (H) variation

The inertia constant H of a synchronous generator quantifies the kinetic energy stored in its rotating components (rotor, turbine shaft, and connected masses) normalized to the machine's rated power output.

Causes of variation

- Rotor Faults:
 - Reduction in rotor mass due to cracks or mechanical imbalance (arising from stress and fatigue)
 - Short-circuits in windings (caused by insulation breakdown, leading to partial or complete loss of excitation)
 - Progressive bearing wear (resulting in higher frictional drag and diminished stored kinetic energy)
- Stator Faults:
 - Winding short-circuits (producing torque pulsations that cause fluctuations in kinetic energy storage)
 - Deformation of the stator core (modifying magnetic reluctance and leading to unstable inertia behavior)
 - Air-gap eccentricity (inducing mechanical oscillations that alter the effective inertia)
- Renewable Integration:
 - Increasing penetration of inverter-based resources (IBRs), which provide no inherent rotational inertia, thereby lowering the aggregate system inertia H

Stability Consequences:

- Frequency Instability:
 - Elevated rate of change of frequency (ROCOF), resulting in more rapid frequency excursions and heightened risk of underfrequency load shedding
- Oscillation Risks:
 - Inconsistent or weakened damping, amplifying inter-area electromechanical oscillations [61]
 - Increased likelihood of loss of synchronism during large disturbances

- Transient Vulnerability:

- Shortened critical clearing time due to altered swing equation dynamics
- Faster rotor angle divergence following fault inception

- Operational Challenges:

- Imbalanced load–generation sharing, complicating governor parameter tuning
- Uneven power allocation across units increases the potential for overload conditions

Monitoring Imperatives:

- Renewable-Dominated Grids:

- Facilitates identification of low-inertia scenarios, enabling timely activation of fast frequency response services [7]

- Fault Prevention:

- Allows early detection of emerging mechanical or electrical degradation in synchronous machines

- Resilience Metrics:

- Supports continuous evaluation of real-time stability margins and system robustness [7, 65]

Load damping coefficient (D) variation

The load damping coefficient, D , quantifies the inherent capability of an interconnected power system to attenuate frequency oscillations and restore rotor speed equilibrium following disturbances [61]. It is mathematically expressed as:

$$D = \frac{\Delta P_d}{\Delta \omega} \quad (5)$$

Where:

- ΔP_d = change in damping (load-sensitive) power,
- $\Delta \omega$ = deviation in rotor (or system) angular speed.

Causes of variation

The load damping coefficient (D) exhibits dynamic behavior and is affected by several key factors:

- Load Composition:

- Loads that are sensitive to frequency changes—such as induction motors and resistive heating elements—contribute positively to damping.

- Loads insensitive to frequency variations—particularly power electronic devices and constant-power equipment—tend to diminish overall damping [61].

- Renewable Integration:

- Inverter-based resources (IBRs) do not possess the natural damping characteristics of conventional synchronous generators.

- Load Dynamics:

- Constant-impedance loads strengthen system damping, whereas constant-power loads weaken it.

Stability Consequences:

- Frequency Oscillations:

- A reduced D value extends the duration of frequency excursions, increasing the likelihood of underfrequency load shedding activation.

- Inter-Area Oscillations:

- Insufficient damping along tie lines can lead to sustained power swings that may escalate into widespread outages.

- Voltage/Angle Instability:

- Inadequate damping aggravates the risk of voltage collapse under conditions of reactive power deficiency.

- Equipment Stress:

- Prolonged oscillatory behavior imposes additional thermal and mechanical stress on transmission lines and transformers, hastening equipment degradation [61].

Monitoring Importance:

- Stability Analysis:

- Reliable estimation of D is essential for conducting accurate transient stability and small-signal stability assessments [66].

- Control Optimization:

- Real-time knowledge of D enables precise tuning of Power System Stabilizers (PSS) and Flexible AC Transmission Systems (FACTS) devices [67].

- Operational Resilience:

- Facilitates implementation of preventive strategies—such as generation redispatch or activation of special protection schemes—to avert cascading events [68].

Problem Formulation

This study focuses on fault detection and parameter estimation within the framework of Load Frequency Control (LFC) for multi-area interconnected power systems. The analysis is based on a representative two-area interconnected power grid, illustrated in **Figure 1**. Although actual power systems display nonlinear and time-dependent behavior, small load perturbations around a steady-state operating condition justify the use of a linearized model. In general, a multi-area power network comprises N LFC areas, each tasked with regulating local frequency and managing inter-area power interchange.

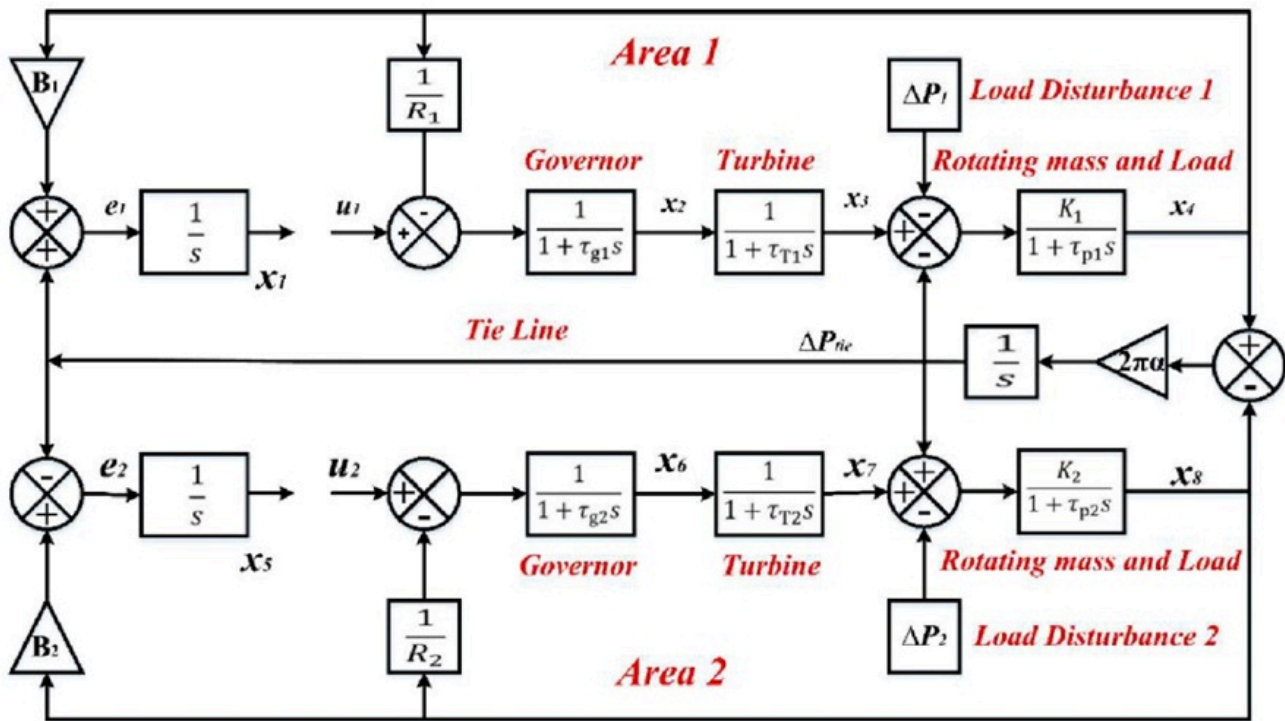


Figure 1. AGC Block Diagram for a Two-Area System.

For each LFC area, the frequency dynamics are governed by the equation:

$$\dot{\Delta f_i} = -\frac{D_i}{H_i} \Delta f_i + \frac{1}{H_i} \Delta P_{mi} - \frac{1}{H_i} \Delta P_{tie,i} - \frac{1}{H_i} \Delta P_{di}, \quad (6)$$

Where Δf_i , ΔP_{di} , D_i , and H_i represent the frequency deviation, load disturbance, equivalent damping coefficient, and equivalent inertia constant, respectively. ΔP_{mi} and $\Delta P_{tie,i}$ denote the mechanical (generator) power output and tie-line power exchange, respectively.

The dynamics governing generator mechanical power and tie-line power flow are expressed as:

$$\begin{aligned} \dot{\Delta P_{mi}} &= -\frac{1}{T_{ti}} \Delta P_{mi} + \frac{1}{T_{ti}} \Delta P_{gi}, \\ \dot{\Delta P_{tie,i}} &= 2\pi \sum_{j \neq i}^N T_{ij} (\Delta f_i - \Delta f_j), \end{aligned} \quad (7)$$

Where T_{ti} is the turbine time constant, T_{ij} is the synchronizing power coefficient between connected areas, N is the total number of control areas, and ΔP_{gi} is the governor valve position change. The governor valve position ΔP_{gi} responds to frequency deviation according to:

$$\dot{\Delta P}_{gi} = -\frac{1}{R_i T_{gi}} \Delta f - \frac{1}{T_{gi}} \Delta P_{gi} - \frac{1}{T_{gi}} u_i, \quad (8)$$

Where R_i and T_{gi} are the speed droop characteristic and governor time constant, respectively, and u_i is the control command issued by the Automatic Generation Control (AGC) system to restore balance between generation and load demand.

By combining Eqs.6–8, the state-space representation for the i -th area becomes:

$$\begin{aligned} \dot{x}_i(t) &= A_{ii} x_i(t) + B_i u_i(t) + \sum_{j \neq i} A_{ij} x_j(t) + F_i \Delta P_{di}(t), \\ y_i(t) &= C_i x_i(t), \end{aligned} \quad (9)$$

Where

$$\begin{aligned} x_i(t) &\triangleq [\Delta f_i \quad \Delta P_{mi} \quad \Delta P_{gi} \quad \Delta P_{tie,i}]^T, \\ A_{ii} &\triangleq \begin{bmatrix} \frac{D_i}{H_i} & \frac{1}{H_i} & 0 & \frac{1}{H_i} \\ 0 & -\frac{1}{T_{ti}} & \frac{1}{T_{ti}} & 0 \\ \frac{1}{R_i T_{gi}} & 0 & -\frac{1}{T_{gi}} & 0 \\ 2\pi \sum_{j \neq i} T_{ij} & 0 & 0 & 0 \end{bmatrix}, \\ A_{ij} &= \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -2\pi T_{ij} & 0 & 0 & 0 \end{bmatrix} \\ B_i &= \begin{bmatrix} 0 & 0 & \frac{1}{T_{gi}} & 0 \end{bmatrix}^T \end{aligned} \quad (10)$$

The overall augmented model for an N -area interconnected power system is then:

$$\dot{X} = AX + B_\omega \omega + BU$$

$$X_i = [\Delta f_i \quad \Delta P_{mi} \quad \Delta P_{gi} \quad \Delta P_{tie,i}]^T$$

$$v = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$$

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1N} \\ A_{21} & A_{22} & \cdots & A_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1} & A_{N2} & \cdots & A_{NN} \end{bmatrix}$$

$$B = \begin{bmatrix} B_1 & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_2 & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B_n \end{bmatrix}$$

$$C = \begin{bmatrix} C_1 & 0_{2 \times 4} & \cdots & 0_{2 \times 4} \\ 0_{2 \times 4} & C_2 & \cdots & 0_{2 \times 4} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{2 \times 4} & 0_{2 \times 4} & \cdots & C_N \end{bmatrix}$$

$$U = \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_N \end{bmatrix}$$

(11)

$$U_i = f(ACE_i)$$

$$ACE_i = \beta_i \Delta f_i + \Delta P_{tie,i}$$

$$\beta_i = \frac{1}{R_i} + D_i \text{ frequency Bias Factor of Area } i,$$

$$C_i = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_{\omega i} = \begin{bmatrix} -\frac{1}{H_i} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$B_{\omega} = \begin{bmatrix} B_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B_{\omega N} \end{bmatrix}$$

$$\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_N \end{bmatrix}$$

$$\omega_i = \Delta P_{di}$$

It should be emphasized that frequency deviation Δf_i and Area Control Error (ACE_i) are continuously measured at each generating unit for protection and control purposes. Phasor Measurement Units (PMUs) provide real-time frequency monitoring, while tie-line power flow meters deliver accurate real-time measurements of interchange power. Consequently, the proposed fault detection and estimation scheme requires no supplementary sensors or additional inter-area measurement signals. Load variations are treated as external disturbance inputs to the system.

H_{∞}/H_2 Pole Placement Control

The H_{∞} norm of a stable transfer function $G(s)$ represents the supremum of its RMS gain over all inputs, equivalent to the peak value of its frequency response magnitude:

$$\|G\|_{\infty} = \sup_{\omega} \sigma_{max}(G(j\omega)) \quad (12)$$

In H_{∞} control design, the primary objective is to minimize the RMS gain from exogenous disturbances ω to the regulated output z within a closed-loop configuration. This effectively reduces the influence of disturbances on overall system behavior (Figure 2).

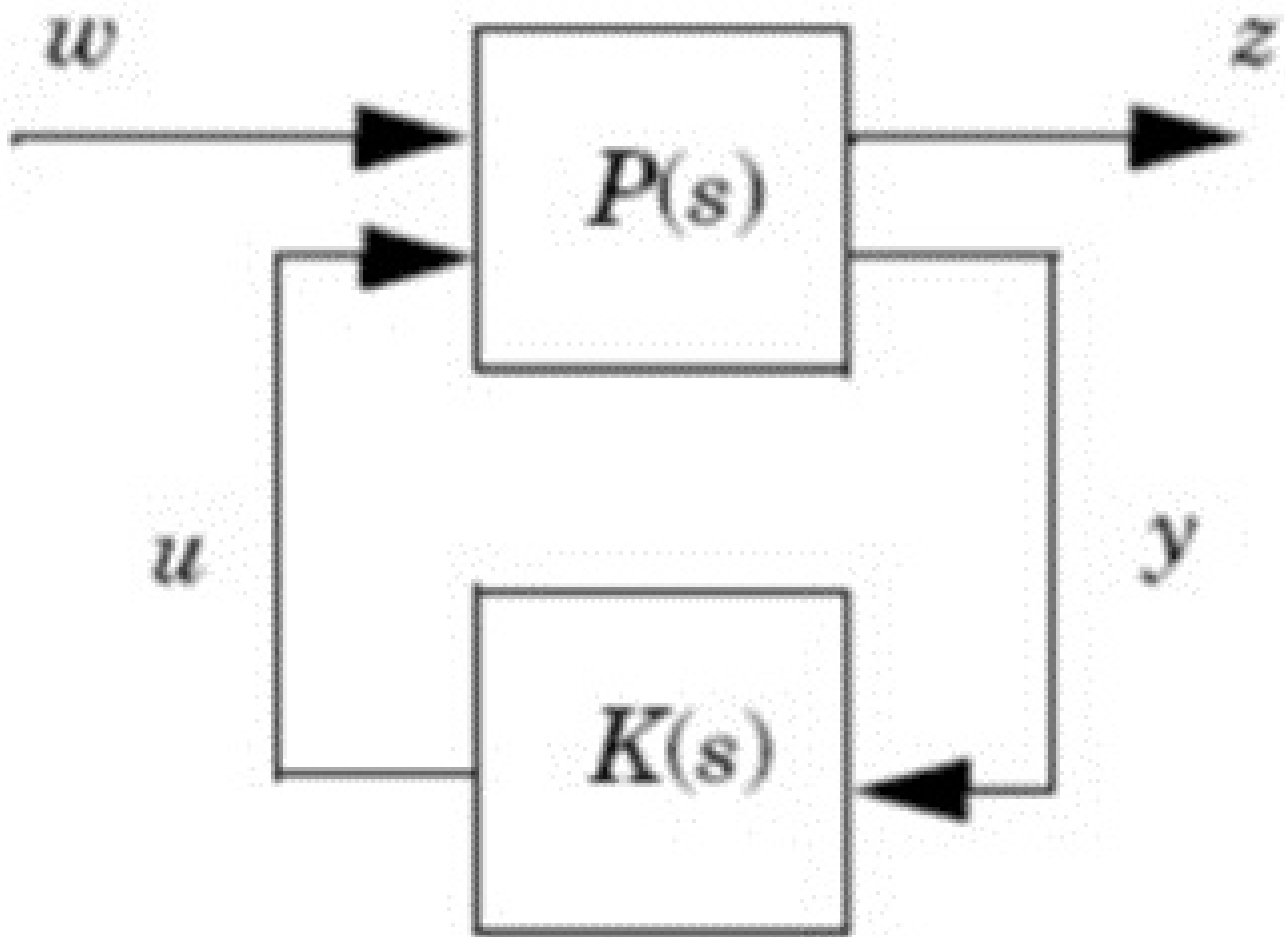


Figure 2. H^∞ feedback control system.

The generalized plant $P(s)$ is structured in partitioned form as:

$$\begin{pmatrix} z(s) \\ y(s) \end{pmatrix}^T = \begin{pmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{pmatrix} \begin{pmatrix} \omega(s) \\ u(s) \end{pmatrix}^T \quad (13)$$

The resulting closed-loop transfer function from ω to z is then:

$$F(P, K) = P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21} \quad (14)$$

Optimal H^∞ control seeks to minimize $\|F(P, K)\|_\infty$ over all stabilizing linear time-invariant controllers $K(s)$. An alternative formulation involves selecting a performance bound γ and determining whether a stabilizing controller $K(s)$ exists such that

$$\|F(P, K)\|_\infty < \gamma \quad (15)$$

H^∞ techniques are also widely employed to synthesize robust controllers that handle unstructured uncertainties (Figure 3).

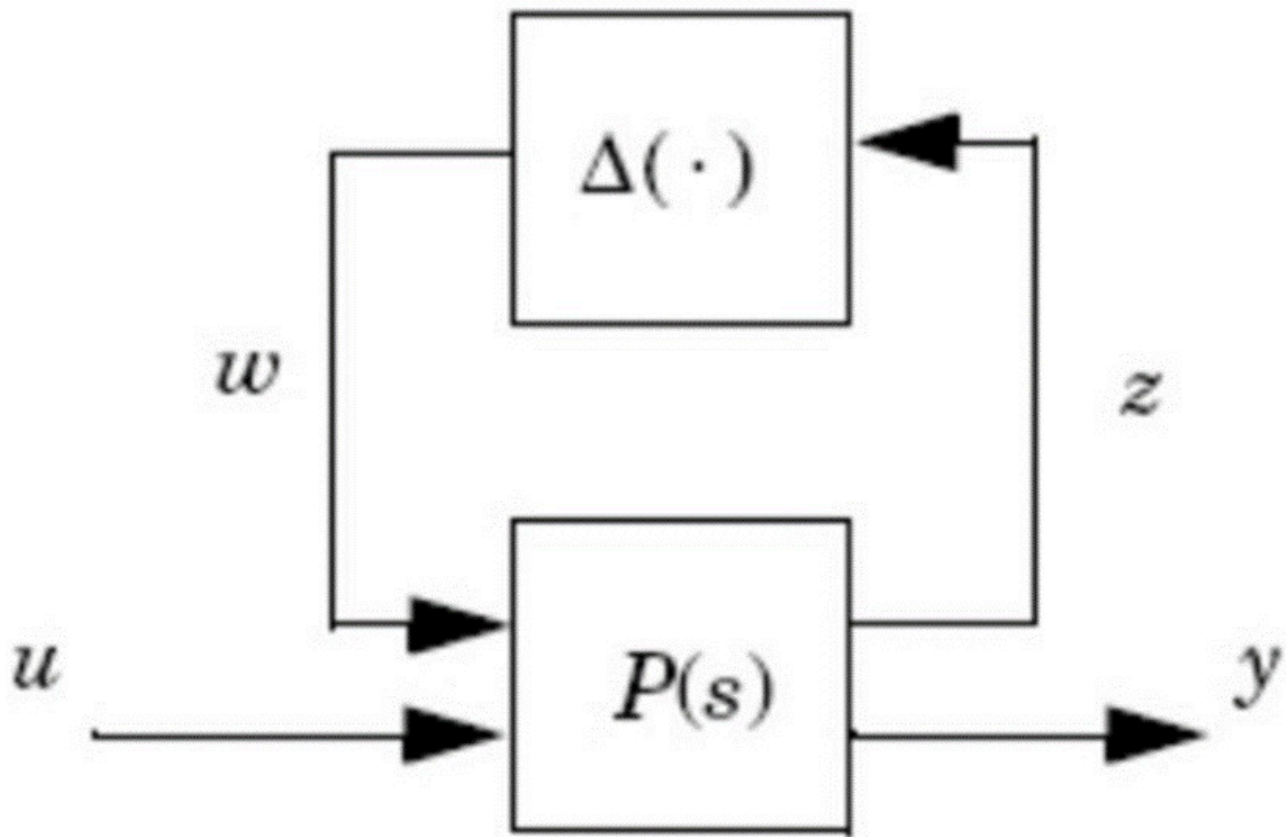


Figure 3. Robust Control Against Unstructured Uncertainties.

Here, the uncertainty block $\Delta(\cdot)$ denotes any bounded-input bounded-output (BIBO) stable system satisfying $\|\Delta\|_\infty < 1$. According to the small-gain theorem, the feedback controller $u = K(s)y$ guarantees robust stability provided the nominal closed-loop transfer function $F(P, K)$ from ω to z satisfies:

$$\|F(P, K)\|_\infty < 1 \quad (16)$$

Riccati and LMI-Based approaches

The Bounded Real Lemma [69] states:

For a continuous-time transfer function $T(s)$ with (not necessarily minimal) state-space realization

$$T(s) = D + C(sI - A)^{-1}B. \quad (17)$$

The following conditions are equivalent:

1. $\|D + C(sI - A)^{-1}B\|_\infty < \gamma$ and the matrix A is Hurwitz (i.e., all eigenvalues have negative real parts);
2. There exists a symmetric positive definite matrix X satisfying the linear matrix inequality (LMI):

$$\begin{pmatrix} A^T X + XA & XB & C^T \\ B^T X & -\gamma I & D^T \\ C & D & -\gamma I \end{pmatrix} < 0. \quad (18)$$

From this lemma, the corresponding H_∞ controller transfer function $K(s)$ takes the form:

$$K(s) = D_K + C_K(sI - A_K)^{-1}B_K. \quad (19)$$

$K(s)$ constitutes a k -th order γ -suboptimal controller if and only if the LMI

$$\begin{pmatrix} A_{cl}^T X_{cl} + X_{cl} A_{cl} & X_{cl} B_{cl} & C_{cl}^T \\ B_{cl}^T X_{cl} & -\gamma I & D_{cl}^T \\ C_{cl} & D_{cl} & -\gamma I \end{pmatrix} < 0. \quad (20)$$

Is feasible for some positive definite $X_{cl} \in \mathbb{R}^{(n+k) \times (n+k)}$.

Optimal H_∞ performance is achieved by directly solving the following convex LMI optimization problem [69]:

Minimize γ subject to $R = R^T$ and $S = S^T$ satisfying:

$$\begin{aligned} \begin{pmatrix} N_{12} & 0 \\ 0 & I \end{pmatrix}^T \begin{pmatrix} AR + RA^T & RC_1^T & B_1 \\ C_1 R & -\gamma I & D_{11} \\ B_1^T & D_{11}^T & -\gamma I \end{pmatrix} \begin{pmatrix} N_{12} & 0 \\ 0 & I \end{pmatrix} < 0 \\ \begin{pmatrix} N_{21} & 0 \\ 0 & I \end{pmatrix}^T \begin{pmatrix} A^T S + SA & SB_1 & C_1^T \\ B_1^T S & -\gamma I & D_{11}^T \\ C_1 & D_{11} & -\gamma I \end{pmatrix} \begin{pmatrix} N_{21} & 0 \\ 0 & I \end{pmatrix} < 0 \\ \begin{pmatrix} R & I \\ I & S \end{pmatrix} \succeq 0 \end{aligned} \quad (21)$$

Where N_{12} and N_{21} represent orthonormal bases for the null spaces of (B_2^T, D_{12}^T) and (C_2, D_{21}) , respectively.

H_∞/H_2 pole placement controller

This paper adopts a combined H_∞ – H_2 controller with regional pole-placement constraints [70, 71]. This design approach exhibits strong robustness to load fluctuations and to parameter deviations caused by modeling errors or environmental factors (e.g., temperature, pressure, humidity, component aging). It further demonstrates resilience against faults affecting key elements such as turbines, governors, transmission lines, system inertia, and damping mechanisms. Accounting for these effects is essential to preserve grid stability and achieve reliable Load Frequency Control (LFC).

To accommodate such uncertainties, the disturbance input vector is augmented to encompass not only load disturbances but also variations in turbine time constant, governor time constant, tie-line synchronizing coefficient (T_{ij}), inertia constant, and damping coefficient.

$$\omega_i = \begin{bmatrix} \Delta P_{di} \\ \Delta T_{Ti} \\ \Delta T_{Gi} \\ \Delta T_{ij} \\ \Delta H_i \\ \Delta D_i \end{bmatrix} \quad (22)$$

The corresponding state-space model, including the extended disturbance vector, is typically written as:

$$\begin{aligned} \dot{x}_i(t) &= (A_{ii} + \Delta A_{ii}) x_i(t) + (B_i + \Delta B_i) u_i(t) \\ &+ \sum_{j \neq i}^N ((A_{ij} + \Delta A_{ij}) x_j(t) + (F_i + \Delta F_i) \Delta P_{di}(t)), \\ d_i(t) &= \Delta A_{ii} x_i(t) + \Delta B_i u_i(t) + \sum_{j \neq i}^N \Delta A_{ij} x_j(t) \\ &+ (F_i + \Delta F_i) \Delta P_{di}(t). \end{aligned} \quad (23)$$

$$\dot{x}_i = A_{ii} x_i + \sum_{j \neq i}^N A_{ij} x_j + B_i u_i + d_i$$

$$\Delta A_{ii} = \frac{\partial A_{ii}}{\partial T_{Ti}} \Delta T_{Ti} + \frac{\partial A_{ii}}{\partial T_{Gi}} \Delta T_{Gi} + \frac{\partial A_{ii}}{\partial T_{Tij}} \Delta T_{Tij} + \frac{\partial A_{ii}}{\partial H_i} \Delta H_i + \frac{\partial A_{ii}}{\partial D_i} \Delta D_i$$

It can be directly verified that:

$$\Delta A_{ii} x_i = \begin{bmatrix} \frac{\Delta D_i \Delta f_i}{H_i} - \frac{\Delta H_i}{H_i^2} (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i}) \\ \frac{\Delta T_{Ti}}{T_{Ti}^2} [\Delta P_{mi} - \Delta P_{gi}] \\ \frac{\Delta T_{Gi}}{T_{Gi}^2} \left[\Delta P_{gi} - \frac{\Delta f_i}{R_i} \right] \\ 2\pi \Delta T_{ij} \cdot \Delta f_i \end{bmatrix}$$

$$\Delta B_i \cdot u_i = \begin{bmatrix} 0 \\ 0 \\ -\frac{\Delta T_{Gi}}{T_{Gi}^2} \cdot u_i \\ 0 \end{bmatrix} \quad (24)$$

$$\Delta A_{ii} X_i + \Delta B_i U + F_i \Delta P_{di} + \sum_{j \neq i}^N (\Delta A_{ij} x_j(t) + \Delta F_i \Delta P_{di}(t)) = B'_{\omega i} \cdot \omega'_i$$

$$= \begin{bmatrix} \frac{\Delta D_i \Delta f_i}{H_i} - \frac{\Delta H_i}{H_i^2} (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i} + \Delta P_{di}) + \frac{\Delta P_{di}}{H_i} \\ \frac{\Delta T_{Ti}}{T_{Ti}^2} [\Delta P_{mi} - \Delta P_{gi}] \\ \frac{\Delta T_{Gi}}{T_{Gi}^2} \left[\Delta P_{gi} - \frac{\Delta f_i}{R_i} \right] - \frac{\Delta T_{Gi}}{T_{Gi}^2} \cdot U \\ 2\pi \Delta T_{ij} (\Delta f_i - \Delta f_j) \end{bmatrix}$$

$$\begin{aligned}
 B'_{\omega i} \cdot \omega'_i &= \begin{bmatrix} \frac{1}{H_i} & -\frac{1}{H_i^2} & \frac{1}{H_i} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{T_{Ti}^2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{T_{Gi}^2} & 0 \\ 0 & 0 & 0 & 0 & 0 & 2\pi \end{bmatrix} \\
 &\cdot \begin{bmatrix} \Delta P_{di} \\ \Delta H_i (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i} + \Delta P_{di}) \\ \Delta D_i \Delta f_i \\ \Delta T_{Ti} [\Delta P_{mi} - \Delta P_{gi}] \\ \Delta T_{Gi} \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right) \\ \Delta T_{Tij} (\Delta f_i - \Delta f_j) \end{bmatrix} \\
 B'_\omega &= \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 4} & \cdots & 0_{4 \times 4} \\ 0_{4 \times 4} & B'_{\omega 2} & \cdots & 0_{4 \times 4} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 4} & 0_{4 \times 4} & \cdots & B'_{\omega N} \end{bmatrix} \\
 \omega'_i &= \begin{bmatrix} \Delta P_{di} \\ \Delta H_i (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i} + \Delta P_{di}) \\ \Delta D_i \Delta f_i \\ \Delta T_{Ti} [\Delta P_{mi} - \Delta P_{gi}] \\ \Delta T_{Gi} \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right) \\ \Delta T_{Tij} (\Delta f_i - \Delta f_j) \end{bmatrix} \\
 \omega' &= \begin{bmatrix} \omega'_1 \\ \omega'_2 \\ \vdots \\ \omega'_N \end{bmatrix}
 \end{aligned}$$

The augmented state-space form for an N-area interconnected power system then becomes:

$$\begin{aligned}
 \dot{X} &= AX + B_\omega \omega + BU \\
 Y &= CX \\
 X_i &= [\Delta f_i \quad \Delta P_{mi} \quad \Delta P_{gi} \quad \Delta P_{tie,i}]^T \\
 X &= \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} \\
 \mathbf{A} &= \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1N} \\ A_{21} & A_{22} & \cdots & A_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1} & A_{N2} & \cdots & A_{NN} \end{bmatrix} \\
 \mathbf{B} &= \begin{bmatrix} B_1 & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_2 & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B_n \end{bmatrix}
 \end{aligned} \tag{25}$$

$$\mathbf{C} = \begin{bmatrix} C_1 & 0_{2 \times 4} & \cdots & 0_{2 \times 4} \\ 0_{2 \times 4} & C_2 & \cdots & 0_{2 \times 4} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{2 \times 4} & 0_{2 \times 4} & \cdots & C_N \end{bmatrix}$$

$$\mathbf{U} = \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_N \end{bmatrix}$$

$$U_i = f(ACE_i)$$

$$ACE_i = \beta_i \Delta f_i + \Delta P_{tie,i}$$

$$\beta_i = \frac{1}{R_i} + D_i \text{ frequency Bias Factor of Area } i,$$

$$C_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B_\omega = \begin{bmatrix} B_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B_{\omega N} \end{bmatrix}$$

$$\omega = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_N \end{bmatrix}$$

LMI formulation for H₂/H_∞ pole placement method

The multi-objective synthesis problem—simultaneously achieving H_∞ and H₂ performance and regional pole placement—is formulated as a set of Linear Matrix Inequalities (LMIs).

System Dynamics

The state-space models of the plant P(s) and controller K(s) are given by:

- Plant:

$$\begin{cases} \dot{x} = Ax \\ + B_1\omega \\ + B_2u \\ z_\infty \\ = C_\infty x \\ + D_{\infty 1}\omega \\ + D_{\infty 2}u \\ z_2 = C_2x \\ + D_{21}\omega \\ + D_{22}u \\ y = C_yx \\ + D_{y1}\omega \end{cases} \quad (26)$$

Where x denotes the state vector, ω the disturbance input, u the control input, and y the measured output.

• Controller:

$$\begin{cases} \dot{\zeta} = A_K\zeta \\ + B_Ky \\ \dot{u} = C_K\zeta \\ + D_Ky \end{cases} \quad (27)$$

Where ζ represents the controller state.

• Closed-loop system:

$$\begin{cases} \dot{x}_{cl} = A_{cl}x_{cl} \\ + B_{cl}\omega \\ z_\infty = C_{cl1}x_{cl} \\ + D_{cl1}\omega \\ z_2 = C_{cl2}x_{cl} \\ + D_{cl2}\omega \end{cases} \quad (28)$$

Where A_{cl} , B_{cl} , C_{cl1} , D_{cl1} , C_{cl2} , and D_{cl2} are the resulting closed-loop matrices.

Design Objectives:

1. H_∞ Performance: The closed-loop RMS gain from ω_∞ to z_∞ must remain below γ . This is ensured by the existence of a symmetric matrix χ_∞ satisfying the LMI [72]:

$$\begin{pmatrix} A_{cl}\chi_{\infty} + \chi_{\infty}A_{cl}^T & B_{cl} & X_{\infty}C_{cl1}^T \\ B_{cl}^T & -I & D_{cl}^T \\ C_{cl1}\chi_{\infty} & D_{cl1} & -\gamma^2 I \end{pmatrix} < 0 \quad (29)$$

$$\chi_{\infty} > 0$$

2. H_2 Performance: The H_2 norm from ω_2 to z_2 must be bounded by ν . When $D_{cl2} = 0$, this constraint is enforced via symmetric matrices χ_2 and Q such that:

$$\begin{pmatrix} A_{cl}\chi_2 + \chi_2A_{cl}^T & B_{cl} \\ B_{cl}^T & -I \end{pmatrix} < 0$$

$$\begin{pmatrix} Q & C_{cl2}\chi_2 \\ \chi_2C_{cl2}^T & \chi_2 \end{pmatrix} > 0 \quad (30)$$

$$\text{Trace}(Q) < \nu^2$$

3. Pole Placement: All closed-loop poles must reside within a specified LMI region defined by:

$$D = \{z \in \mathbb{C} : L + Mz + M^T\bar{z} < 0\} \quad (31)$$

$$L = L^T = \{\lambda_{ij}\}_{1 \leq i, j \leq m} \text{ and } M = \{\mu_{ij}\}_{1 \leq i, j \leq m}$$

Where L and M characterize the desired region in the complex plane, this condition holds if and only if there exists a symmetric matrix χ_{pol} satisfying:

$$[\lambda_{ij} \chi_{pol} + \mu_{ij}A_{cl}\chi_{pol} + \mu_{ij}X_{pol}A_{cl}^T]_{1 \leq i, j \leq m} < 0 \quad (32)$$

$$\chi_{pol} > 0$$

For computational tractability, a common Lyapunov matrix is introduced:

$$\chi = \chi_{\infty} = \chi_2 = \chi_{pol}$$

By applying a change of variables and factorizing χ , $\chi = \chi_1\chi_2^{-1}$, $\chi_1 = \begin{pmatrix} R & I \\ M^T & 0 \end{pmatrix}$; $\chi_2 = \begin{pmatrix} 0 & S \\ I & N^T \end{pmatrix}$;

$$\begin{cases} B_K = NB_K + SB_2D_K \\ C_K = C_KM^T + D_KC_YR \\ A_K = NA_KM^T + NB_KC_YR + SB_2C_KM^T + S(A + B_2D_KC_Y)R \end{cases} \quad (33)$$

The constraints on χ are converted into LMIs in the decision variables R , S , Q , A_K , B_K , C_K , and D_K . This yields the following suboptimal multi-objective LMI synthesis problem [72–74]:

Minimize $\alpha\gamma^2 + \beta \text{Trace}(Q)$ subject to R , S , Q , A_K , B_K , C_K , D_K , and γ^2 satisfying:

$$\begin{pmatrix} AR + RA^T + B_2 C_K + C_K^T B_2^T & A_K^T + A + B_2 D_K C_Y & B_1 + B_2 D_K D_{y1} & H \\ H & A^T S + SA + B_K C_Y + C_Y^T B_K^T & SB_1 + B_K D_{y1} & H \\ H & H & -I & H \\ C_{\alpha} R + D_{\alpha 2} C_K & C_{\alpha} + D_{\alpha 2} D_K C_K & D_{\alpha 1} + D_{\alpha 2} D_K D_{y1} & -\gamma^2 I \end{pmatrix} < 0$$

$$\begin{pmatrix} Q & C_2 R + D_{22} C_K & C_2 + D_{22} D_K C_Y \\ H & R & I \\ H & I & S \end{pmatrix} > 0 \quad (34)$$

$$\left[\lambda_{ij} \begin{pmatrix} R & I \\ I & S \end{pmatrix} + \mu_{ij} \begin{pmatrix} AR + B_2 C_K & A + B_2 D_K C_Y \\ A_K & SA + B_K C_Y \end{pmatrix} + \mu_{ji} \begin{pmatrix} RA^T + C_K^T B_2^T & A_K^T \\ (A + B_2 D_K C_Y)^T & A^T S + C_Y^T B_K^T \end{pmatrix} \right]_{1 \leq i, j \leq m_{ij}} < 0$$

Let γ^* and Q^* denote the optimal values obtained from this LMI problem. The closed-loop H_{∞} and H_2 performance levels are then guaranteed to satisfy: $\gamma \leq \gamma^*$ and the H_2 norm $\leq \sqrt{\text{Trace}(Q^*)}$.

$$\|T_{\infty}\|_{\infty} \leq \gamma^* \quad \|T_2\|_2 \leq \sqrt{\text{Trace}(Q^*)} \quad (35)$$

Limitations of H_{∞} synthesis

In numerous control engineering applications, standalone H_{∞} synthesis encounters inherent restrictions. It primarily focuses on ensuring closed-loop stability and attenuating worst-case disturbances, while placing less emphasis on other essential performance criteria, such as noise suppression and desirable time-domain behavior. Specifications related to energy minimization and average-case performance are typically better handled through Linear Quadratic Gaussian (LQG) techniques or H_2 -norm optimization, which prioritize overall energy reduction rather than purely worst-case bounds. Furthermore, conventional H_{∞} design lacks explicit mechanisms for directly constraining pole locations, a feature critical for tailoring transient response properties, such as settling time, overshoot, and damping.

To address these drawbacks, multi-objective control synthesis is often preferred, integrating both H_{∞} and H_2 performance objectives with regional pole-placement constraints. This combined strategy enables concurrent optimization of disturbance rejection, noise rejection, and transient dynamics. In the present context, since the control input vector serves as a mathematical estimator rather than a physical actuator command, an explicit H_2 constraint is unnecessary. Consequently, the error estimator is formulated as a mixed H_{∞} pole-placement observer. Simulation results demonstrate that this design outperforms the conventional pure H_{∞} observer previously employed in similar applications.

Error dynamics in state-space representation

For observer design targeting the augmented system given in Eq. 11, the state estimator is first defined as:

$$\begin{aligned}\dot{\widehat{X}} &= A \cdot \widehat{X} + B \cdot U - U_x \\ \widehat{Y} &= C \cdot \widehat{X} - U_y\end{aligned}\quad (36)$$

$$\text{Where: } U_x = [U_{x1} \ U_{x2} \ U_{x3} \ U_{x4}]^T; U_y = [U_{y1} \ U_{y2}]^T;$$

The corresponding error dynamics in state-space form are then expressed as:

$$\begin{aligned}\dot{e}_x &= A \cdot e_x + B'_{\omega i} \cdot \omega'_i + U_x \\ e_y &= C \cdot e_x + U_Y\end{aligned}\quad (37)$$

$$\text{Where: } e_x = X - \widehat{X}, \ e_y = Y - \widehat{Y}$$

Here, U_x denotes the control vector employed to compensate for actuator faults, while U_y serves as the control vector to compensate for sensor faults.

A generic controlled system can be represented in the form:

$$\begin{aligned}\dot{X} &= A \cdot X + B_1 \cdot \omega + B_2 \cdot U_C \\ z &= C_1 \cdot X + D_{11} \cdot \omega + D_{12} \cdot U_C \\ Y &= C_2 \cdot X + D_{21} \cdot \omega + D_{22} \cdot U_C\end{aligned}\quad (38)$$

Where:

- X is the state vector,
- ω is the disturbance vector,
- z is the regulated (controlled) output vector,
- Y is the measured output vector, and
- U_C is the control input vector.

In the present framework, we assign $e_x = X$ and $e_y = Y$. Comparing this structure with the error dynamics of the augmented battery/power system model yields the disturbance input matrix $B_1 = B'_{\omega i}$, with the disturbance vector $\omega = \omega'$.

The control input vector is defined as: $U_C = [U_{x1} \ U_{x2} \ U_{x3} \ U_{x4} \ U_{y1} \ U_{y2}]^T$

$$\begin{aligned}
 B_2 &= [I_{4 \times 4} \quad 0_{4 \times 2}]^T, \\
 C_2 &= C, \quad D_{21} = [0_{2 \times 6}], \\
 D_{22} &= [0_{2 \times 4} \quad I_{2 \times 2}], \\
 z &= \begin{bmatrix} e_x \\ e_y \end{bmatrix}, C_1 = \begin{bmatrix} I \\ C \end{bmatrix}, D_{11} = \begin{bmatrix} 0_{4 \times 6} \\ D_{21} \end{bmatrix}, D_{12} = \begin{bmatrix} 0_{4 \times 6} \\ D_{22} \end{bmatrix}
 \end{aligned} \tag{39}$$

The choice of appropriate control laws UC enables the driving of both e_x and e_y to zero, thereby facilitating reliable detection of actuator faults (e.g., deviations in turbine time constant ΔT_{ti} , governor time constant ΔT_{gi} , synchronizing coefficient ΔT_{ij} , etc.) and sensor faults (Figure 4).

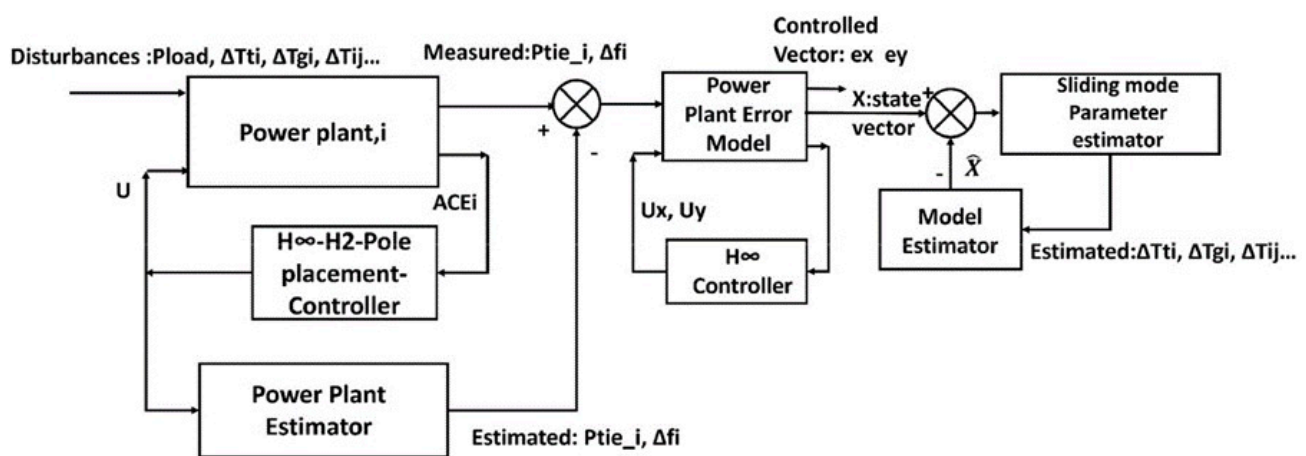


Figure 4. Observer based on H_∞ pole placement controller.

The regulated error signals e_x and e_y are utilized to identify and isolate both actuator-related parameter variations and sensor malfunctions.

Sliding Mode Adaptive Estimator

This section assumes that the H_∞ pole-placement observer has already provided accurate state estimates. The subsequent task involves online estimation of all relevant system parameters, which is achieved using a sliding-mode adaptive estimator.

The interconnected power system, subject to disturbances arising from parameter drifts (due to aging, temperature variations, or faults), can be modeled as:

$$\begin{aligned}
 \dot{x} &= \delta(x, u) + \varphi(x, u) + B(t - T)f(x, U, t) \\
 y &= x
 \end{aligned} \tag{40}$$

Where $\delta(x, u) = A x + B U$ is the nominal dynamics as defined in Eq. 11, and $f(x, U, t) = B \omega$ ω represents the fault/disturbance function as given in Eqs. 24.

Here, U denotes the input vector incorporating disturbance-related parameter changes, $K = [\Delta P_{load}, \Delta T_{ti}, \Delta T_{gi}, \Delta T_{tij}, \Delta H_i, \Delta D_{ij}]$. The term $\delta(x, u)$ captures the nominal (healthy) system behavior, whereas $\varphi(x, u)$ accounts for model uncertainties or unmodeled dynamics.

A time profile characterizes the onset of a fault due to parameter drift:

$B(t-T) = \text{diag}(\beta_1(t-T_1), \dots, \beta_n(t-T_n))$, where each $\beta_i(t)$ ($i=1, \dots, n$) is a step function.

Assumptions:

1. All system states are measurable (or accurately estimated via the H_∞ /pole-placement observer).
2. Model uncertainty is bounded, i.e., $|\varphi_i(x, u)| \leq \bar{\varphi}_i$, where $\varphi_i(x, u)$ for the i th component ($i=1, \dots, n$), where $\bar{\varphi}_i > 0$ is a known positive constant.

Under these assumptions, the sliding mode adaptive observer is constructed as:

$$\dot{\hat{x}} = -\Lambda \hat{x} + \Lambda x + \delta(x, u) + M(\tilde{x}) + \hat{f}(x, u, \hat{\theta}) \quad (41)$$

Where $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ with $\lambda_i > 0$ ($i=1, \dots, n$) is a diagonal matrix to be designed, such that $-\Lambda$ defines the observer error dynamics eigenvalues.

$\hat{f}(x, u, \hat{\theta}) = [\hat{f}^1(x, u, \hat{\theta}^1), \dots, \hat{f}^n(x, u, \hat{\theta}^n)]$ is the adaptive online approximation of the fault function, with $\hat{\theta}_i$ representing the estimated parameter vector for the i -th component. The estimation error is defined as:

$$\tilde{x} = x - \hat{x} = [\tilde{x}_1, \dots, \tilde{x}_n]^T \quad (42)$$

Which serves to reconstruct the fault function using $\hat{\theta}_i \in \mathbb{R}^{p_i}$ ($i=1, \dots, n$).

The sliding mode term $M(\tilde{x}) = [M_1(\tilde{x}_1), M_2(\tilde{x}_2), \dots, M_n(\tilde{x}_n)]^T$ incorporates a boundary layer to reduce chattering effects [68] and is given by:

$$M_i(\tilde{x}_i) = \begin{cases} \bar{\varphi}_i \text{sign}(\tilde{x}_i) & \text{if } |\tilde{x}_i| > \eta_i \\ \bar{\varphi}_i \tilde{x}_i / \eta_i & \text{if } |\tilde{x}_i| \leq \eta_i \end{cases} \quad (43)$$

Where $\eta_i > 0$ ($i=1, \dots, n$) is a small positive boundary layer thickness satisfying $\eta_i \ll \bar{\varphi}_i$.

Theorem 1 [75]

Assuming $\tilde{x}_i(t_0) = 0$ (according to Assumption 1), before fault occurrence, the state estimation error remains bounded by $|\tilde{x}_i| \leq \epsilon_i$ ($i = 1, \dots, n$), where

$$\epsilon_i = \min \left[\left(\frac{1}{2} \right) \sqrt{\eta_i \cdot \varphi_i / \lambda_i}, \eta_i \right] \quad (44)$$

In practice, since $\eta_i \ll \bar{\varphi}_i$, the bound simplifies to $\epsilon_i = \eta_i$.

Based on Theorem 1, the robust fault detection logic is as follows:

- If $|\tilde{x}_i| \leq \varepsilon_i$ for all $(i = 1 \dots n)$, then no fault is declared.
- If $|\tilde{x}_i| > \varepsilon_i$ for the first time, a fault is detected in the i th subsystem, and the adaptive update law is activated:

$$\begin{aligned} \dot{\hat{\theta}}_i &= \begin{cases} \Gamma_i \left(-k_i \hat{\theta}_i + \Omega_i \tilde{x}_i \right) & \text{if } |\tilde{x}_i| > \varepsilon_i \\ 0 & \text{if } |\tilde{x}_i| \leq \varepsilon_i \end{cases} \\ \hat{\theta}_i(t_0) &= 0 \quad (i = 1, \dots, n) \end{aligned} \quad (45)$$

Where $\Gamma_i \in \mathbb{R}^{p_i \times p_i} > 0$ is the adaptation gain matrix, $k_i > 0$ is a small positive feedback coefficient, and $\Omega_i = \partial f_i(x, u, t) / \partial \theta_i$.

The additional leakage term $-k_i \hat{\theta}_i$ improves robustness against bounded disturbances via σ -modification [58] (Narendra & Annaswamy, 1989).

Assumption 2: $\|\theta_i\| \leq \theta_i^*$, $\|\theta_i^*\| \leq \theta_i^* = 1, \dots, n$

Theorem 2

(Stability) [75]:

Let $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$ denote the parameter estimation error for the i th component. Under the proposed adaptive update law and Assumption 2, both the state and parameter estimation errors remain uniformly bounded for all time.

Theorem 3: (Detectability) [75]:

A sufficient condition for reliable fault detection is $|f_i(x, u, t)| > 2\varphi_i$

Noise model and assumptions

Disturbances are modeled in discrete time as comprising two independent components:

$$\begin{aligned} x_{k+1} &= (A(\theta) + \Delta A - f) \cdot x_k + (B + \Delta B - f) \cdot u_k + G d_k + W w_k, \\ y_k &= C x_k + v_k, \end{aligned} \quad (46)$$

Where

- w_k represents process noise and v_k represents measurement noise. For analytical purposes and when deriving probabilistic expressions for the false alarm rate (FAR), w_k and v_k are assumed to be zero-mean Gaussian white noise sequences (uncorrelated over time) with known covariance matrices Q_w and R_v , respectively. In the deterministic H_∞ synthesis framework, however, w_k and v_k are treated simply as energy-bounded disturbances.
- Exogenous unknown inputs d_k (e.g., sudden load changes) are regarded as bounded or energy-limited signals during the H_∞ controller/observer design.

Fault model

Faults are represented as deviations in the plant parameters $\theta = \{T_g, T_t, H, D, T_{ij}\}$. Following local linearization around an operating point, a small parameter shift $\Delta\theta$ manifests as a structured additive perturbation in the state and/or input matrices. Consequently, in the observer error dynamics, such faults appear as persistent, structured disturbances—typically exhibiting low-frequency or step-like behavior on the residual signal. In contrast, sensor attacks or biases would introduce direct additive terms into the measurement vector y_k .

$$\begin{cases} A(\theta + \Delta\theta) = A(\theta) + \frac{\partial A}{\partial \theta} \cdot \Delta\theta = A + \Delta A - f \\ B(\theta + \Delta\theta) = B(\theta) + \frac{\partial B}{\partial \theta} \cdot \Delta\theta = B + \Delta B - f \end{cases} \quad (47)$$

How we distinguish noise from faults

The proposed Fault Detection and Isolation (FDI) scheme relies on a two-stage separation strategy:

1. H_∞ observer (frequency-domain separation): The mixed H_∞/H_2 pole-placement observer is designed with frequency-dependent weighting functions that function as low-pass filters on the estimation error channels. This design amplifies low-frequency content while strongly suppressing high-frequency components. Since measurement and process noise predominantly occupy higher frequency bands, they are effectively attenuated. Parameter faults, however, produce persistent or step-like changes that appear as low-frequency signatures in the residual and remain clearly detectable.
2. Sliding-Mode Estimator (SME) / amplitude-stage: A bank of sliding-mode estimators projects the filtered residual from the H_∞ stage onto parameter-specific sensitivity directions and applies an amplitude threshold (boundary layer) ϕ_i for each parameter channel i . Residuals falling below ϕ_i are discarded as noise; those exceeding ϕ_i are flagged as potential faults and subjected to persistence checks for confirmation.

This cascaded architecture—low-pass H_∞ filtering followed by amplitude thresholding in the SME—substantially reduces false alarms caused by high-frequency noise while minimizing chattering or spurious triggers from minor residual fluctuations.

False alarm rate (FAR) formulation

The H_∞ synthesis yields a guaranteed disturbance attenuation level γ . Assuming known upper bounds on the disturbances $(\bar{w}, \bar{v}, \bar{d})$, a conservative residual envelope τ can be derived, which in turn informs the choice of threshold ϕ_i . This approach ensures $\text{FAR} = 0$ for all disturbances within their prescribed bounds, albeit at the cost of conservatism.

Threshold design criteria

The threshold η employed in the current implementation is determined from the worst-case performance bound provided by the H_∞ observer synthesis. The key design criteria include:

- The H_∞ optimization minimizes the induced gain from the disturbance input $w(t)$ to the residual output $r(t)$, guaranteeing:

$$\|T_{w \rightarrow r}\|_\infty < \gamma \quad (48)$$

Where γ is the attained H_∞ norm. This establishes a theoretical upper limit on residual energy under any energy-bounded disturbance:

$$\sum_{k=0}^{\infty} \|r_k\|_2^2 \leq \gamma^2 \sum_{k=0}^{\infty} \left(\|w_k\|_2^2 + \|v_k\|_2^2 + \|d_k\|_2^2 \right), \quad (49)$$

Here, $r_k := y_k - C\hat{x}_k$ denotes the residual signal.

- Using the assumed disturbance bounds $(\overline{w}, \overline{v}, \overline{d})$, a conservative residual bound τ is computed. The threshold η is then selected to exceed this worst-case residual magnitude:

$$\eta = \kappa \cdot \gamma \cdot E[\|w(t)\|_2] \quad (50)$$

Where $\kappa > 1$ is a safety margin (typically chosen between 1.5 and 2) to accommodate modeling uncertainties, and $E[\|w(t)\|_2^2]$ reflects the expected disturbance energy derived from historical fault-free operating data.

This deterministic, worst-case threshold design directly influences the false alarm rate as follows:

Deterministic Guarantee: Provided that all actual disturbances remain within their assumed energy bounds $(\|w(t)\|_2 \leq \overline{w})$, the residual $r(t)$ will never surpass the threshold η in the absence of a fault. Consequently, under ideal adherence to these bounds, the design ensures a false alarm rate (FAR) of 0.

Practical Consequences and Trade-offs:

- **Conservative Design:** The high threshold required to cover worst-case scenarios also increases the Minimum Detectable Fault (MDF) magnitude, potentially leading to missed detections of small or incipient faults.
- **Vulnerability to Unmodeled Dynamics:** The H_∞ bound holds only for disturbances that conform precisely to the modeled characteristics. Any unmodeled disturbance exceeding the bound $\overline{w}$ can drive $r(t) > \eta$, producing a false alarm. The purely deterministic framework lacks a probabilistic mechanism to quantify or mitigate this risk.

Mathematical formulation for a tunable FAR

To address the aforementioned limitation, future extensions of this work will incorporate a probabilistic thresholding approach [52, 76]. This strategy shifts away from a strict worst-case deterministic bound toward a stochastic formulation:

- Under the null hypothesis (H_0 : no fault present), the residual r_k is modeled as zero-mean Gaussian white noise with covariance matrix Σ_r .
- A whitened, windowed test statistic is defined as:

$$J_k^{(m)} = \sum_{t=k-m+1}^k \mathbf{r}_t^\top \Sigma_r^{-1} \mathbf{r}_t \quad (51)$$

Under H_0 , $J_k^{(m)} \sim \chi^2_{mp}$ follows a χ^2 distribution with $m \times p$ degrees of freedom, where $p = \dim(r)$.

The threshold η_α is then set using the inverse cumulative distribution function for a desired FAR α :

$$\eta_\alpha = F_{\chi^2_{mp}}^{-1}(1 - \alpha) \quad (52)$$

This formulation provides an explicit mathematical relationship for the false alarm rate:

$$\text{FAR} = P\left(J_k^{(m)} > \eta_\alpha | H_0\right) = \alpha. \quad (53)$$

In essence, the present threshold design prioritizes robustness, providing a deterministic guarantee of $\text{FAR} = 0$ under idealized bounded disturbance conditions. In forthcoming developments, integration of the probabilistic χ^2 -based test will be pursued. This enhancement will empower operators to directly specify an acceptable FAR level α (e.g., 1 %), converting the threshold from a fixed, conservative value into an adjustable parameter. Such tunability will enable a flexible trade-off between detection sensitivity and specificity, tailored to specific operational requirements, thereby markedly improving the real-world applicability of the proposed FDI framework.

Fault Detection and Isolation

To achieve precise detection and isolation of individual faults, the analysis assumes that only a single fault is active at any given time. For each possible fault type, a dedicated observer is synthesized by appropriately selecting the corresponding disturbance input matrix $B\omega'$. Five specialized estimators are constructed, each designed to estimate the effect of a specific fault under the assumption that it arises from variation in the associated parameter (Figure 5). Upon fault occurrence, all five estimators produce parameter estimates simultaneously. The estimator aligned with the true fault yields accurate parameter values, whereas the mismatched estimators yield either inconsistent but plausible estimates or clearly erroneous results (e.g., negative or unbounded). Estimators producing physically invalid outputs are discarded, while the remaining candidates are retained. When the set of valid estimators collectively produces a distinct signature unique to each fault type, effective fault isolation is confirmed.

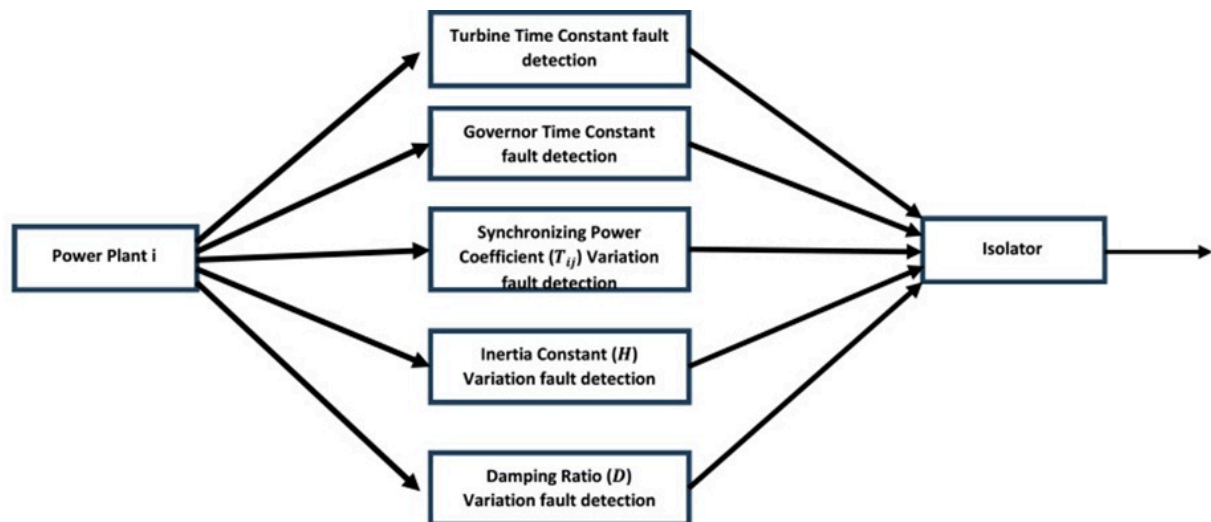


Figure 5. Isolators.

Five separate simulation runs were conducted for each fault scenario, with the responses of all fault detectors recorded and presented in Figures 6-11.

Turbine time constant estimator and isolator

Consider a fault manifesting as a variation ΔT_{Ti} in the turbine time constant. The corresponding disturbance vector becomes:

$$\begin{aligned}
 B'_{\omega i} \cdot \omega'_i &= \begin{bmatrix} 0 \\ \frac{1}{T_{Ti}^2} \\ 0 \\ 0 \end{bmatrix} \cdot \Delta T_{Ti} [\Delta P_{mi} - \Delta P_{gi}] ; B'_{\omega} \\
 &= \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B'_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B'_{\omega N} \end{bmatrix} ; \\
 \omega'_i &= \Delta T_{Ti} [\Delta P_{mi} - \Delta P_{gi}] \\
 \omega' &= \begin{bmatrix} \omega'_1 \\ \omega'_2 \\ \vdots \\ \omega'_N \end{bmatrix}
 \end{aligned} \tag{54}$$

The sliding mode estimator gain vector for Eq. 54 is then given by:

$$\Omega_i = \frac{\partial f_i(x, U, t)}{\partial \theta_i} = \frac{\partial \begin{bmatrix} 0 \\ \frac{1}{T_{Ti}^2} \\ 0 \\ 0 \end{bmatrix} \cdot \Delta T_{Ti} [\Delta P_{mi} - \Delta P_{gi}]}{\partial \Delta T_{Ti}} = \begin{bmatrix} 0 \\ \frac{[\Delta P_{mi} - \Delta P_{gi}]}{T_{Ti}^2} \\ 0 \\ 0 \end{bmatrix} \tag{55}$$

Governor time constant estimator and isolator

Consider a fault manifesting as a variation ΔT_{Gi} in the governor time constant. The corresponding disturbance vector becomes:

$$\begin{aligned}
 B'_{\omega i} \cdot \omega'_i &= \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_{Gi}^2} \\ 0 \end{bmatrix} \Delta T_{Gi} \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right); B'_{\omega} \\
 &= \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B'_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B'_{\omega N} \end{bmatrix} \\
 \omega'_i &= \Delta T_{Gi} \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right) \\
 \omega' &= \begin{bmatrix} \omega'_1 \\ \omega'_2 \\ \vdots \\ \omega'_N \end{bmatrix}
 \end{aligned} \tag{56}$$

The sliding mode estimator gain vector for Eq. 56 is then given by:

$$\Omega_i = \frac{\partial f_i(x, U, t)}{\partial \theta_i} = \frac{\partial \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_{Gi}^2} \\ 0 \end{bmatrix} \Delta T_{Gi} \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right)}{\partial \Delta T_{Gi}} = \begin{bmatrix} 0 \\ \left(\Delta P_{gi} - \frac{\Delta f_i}{R_i} - U \right) \\ \frac{1}{T_{Gi}^2} \\ 0 \end{bmatrix} \tag{57}$$

Synchronizing power coefficient (Tij) estimator and isolator

Consider a fault manifesting as a variation ΔT_{ij} in the synchronizing power coefficient (Tij). The corresponding disturbance vector becomes:

$$\begin{aligned}
 B'_{\omega i} \cdot \omega'_i &= \begin{bmatrix} 0 \\ 0 \\ 0 \\ 2\pi \end{bmatrix} \cdot \Delta T_{Tij} (\Delta f_i - \Delta f_j); B'_{\omega} \\
 &= \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 4} & \cdots & 0_{4 \times 4} \\ 0_{4 \times 4} & B'_{\omega 2} & \cdots & 0_{4 \times 4} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 4} & 0_{4 \times 4} & \cdots & B'_{\omega N} \end{bmatrix} \\
 \omega'_i &= \Delta T_{Tij} (\Delta f_i - \Delta f_j). \\
 \omega' &= \begin{bmatrix} \omega'_1 \\ \omega'_2 \\ \vdots \\ \omega'_N \end{bmatrix}
 \end{aligned} \tag{58}$$

The sliding mode estimator gain vector for Eq. 58 is then given by:

$$\Omega_i = \frac{\partial f_i(x, U, t)}{\partial \theta_i} = \frac{\partial \begin{bmatrix} 0 \\ 0 \\ 0 \\ 2\pi \end{bmatrix} \cdot \Delta T_{Tij} (\Delta f_i - \Delta f_j)}{\partial \Delta T_{Tij}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 2\pi (\Delta f_i - \Delta f_j) \end{bmatrix} \tag{59}$$

Inertia constant H estimator and isolator

Consider a fault manifesting as a variation ΔH_i in the inertia constant (H_i). The corresponding disturbance vector becomes:

$$\begin{aligned}
 B'_{\omega i} \cdot \omega'_i &= \begin{bmatrix} -\frac{1}{H_i^2} \\ 0 \\ 0 \\ 0 \end{bmatrix} \Delta H_i (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i} + \Delta P_{di}); \\
 B'_{\omega} &= \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B'_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B'_{\omega N} \end{bmatrix} \\
 \omega'_i &= \Delta H_i (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{tie,i} + \Delta P_{di}) \\
 \omega' &= \begin{bmatrix} \omega'_1 \\ \omega'_2 \\ \vdots \\ \omega'_N \end{bmatrix}
 \end{aligned} \tag{60}$$

The sliding mode estimator gain vector for Eq. 60 is then given by:

$$\begin{aligned}\Omega_i &= \frac{\partial f_i(x, U, t)}{\partial \theta_i} = \frac{\partial \begin{bmatrix} -\frac{1}{H_i^2} \\ 0 \\ 0 \\ 0 \end{bmatrix} \Delta H_i (D_i \Delta f_i + \Delta P_{mi} + \Delta P_{lre,i} + \Delta P_{di})}{\partial \Delta H_i} \\ &= \begin{bmatrix} -\frac{(D_i \Delta f_i + \Delta P_{mi} + \Delta P_{lre,i} + \Delta P_{di})}{H_i^2} \\ 0 \\ 0 \\ 0 \end{bmatrix}\end{aligned}\quad (61)$$

Damping ratio estimator and isolator

Consider a fault manifesting as a variation ΔD_i in the damping coefficient (D_i). The corresponding disturbance vector becomes:

$$\begin{aligned}B'_{\omega_i} \cdot \omega'_i &= \begin{bmatrix} \frac{1}{H_i} \\ 0 \\ 0 \\ 0 \end{bmatrix} \cdot \Delta D_i \Delta f_i; B'_{\omega} = \begin{bmatrix} B'_{\omega 1} & 0_{4 \times 1} & \cdots & 0_{4 \times 1} \\ 0_{4 \times 1} & B'_{\omega 2} & \cdots & 0_{4 \times 1} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{4 \times 1} & 0_{4 \times 1} & \cdots & B'_{\omega N} \end{bmatrix} \\ \omega'_i &= \Delta D_i \Delta f_i \\ \omega &= \begin{bmatrix} \vdots \\ \omega'_N \end{bmatrix}\end{aligned}\quad (62)$$

The sliding mode estimator gain vector for Eq. 62 is then given by:

$$\Omega_i = \frac{\partial f_i(x, U, t)}{\partial \theta_i} = \frac{\partial \begin{bmatrix} \frac{1}{H_i} \\ 0 \\ 0 \\ 0 \end{bmatrix} \cdot \Delta D_i \Delta f_i}{\partial \Delta D_i} = \begin{bmatrix} \frac{\Delta f_i}{H_i} \\ 0 \\ 0 \\ 0 \end{bmatrix}\quad (63)$$

Simulations

Simulation results demonstrate that the H_∞ observer is capable of estimating the system states with reasonable accuracy, as depicted in Figure 6. That said, the settling behavior during the transient phase tends to be pronounced and varies noticeably depending on the choice of initial conditions. In comparison, the combined H_∞ with pole-placement observer

achieves markedly faster settling and smoother convergence across all starting conditions tested. As a result, this enhanced observer design has been chosen for the state estimation task, and its output states are then passed to the sliding-mode-based estimator for fault parameter identification.

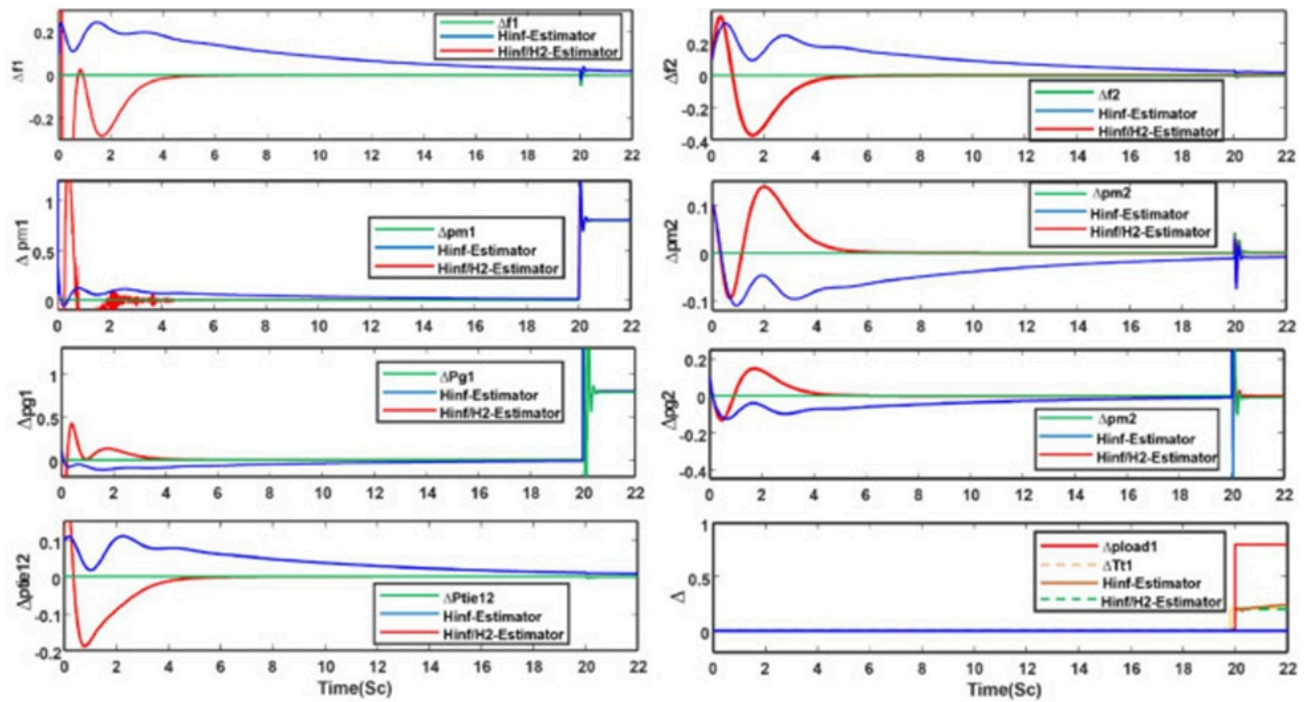


Figure 6. Comparison between the H^∞ observer and the H^∞ -pole placement observer for different initial conditions.

Simulations were carried out using five separate estimators, each applied to one of five distinct fault types. The time responses are illustrated in five dedicated figures (Figures 7-11).

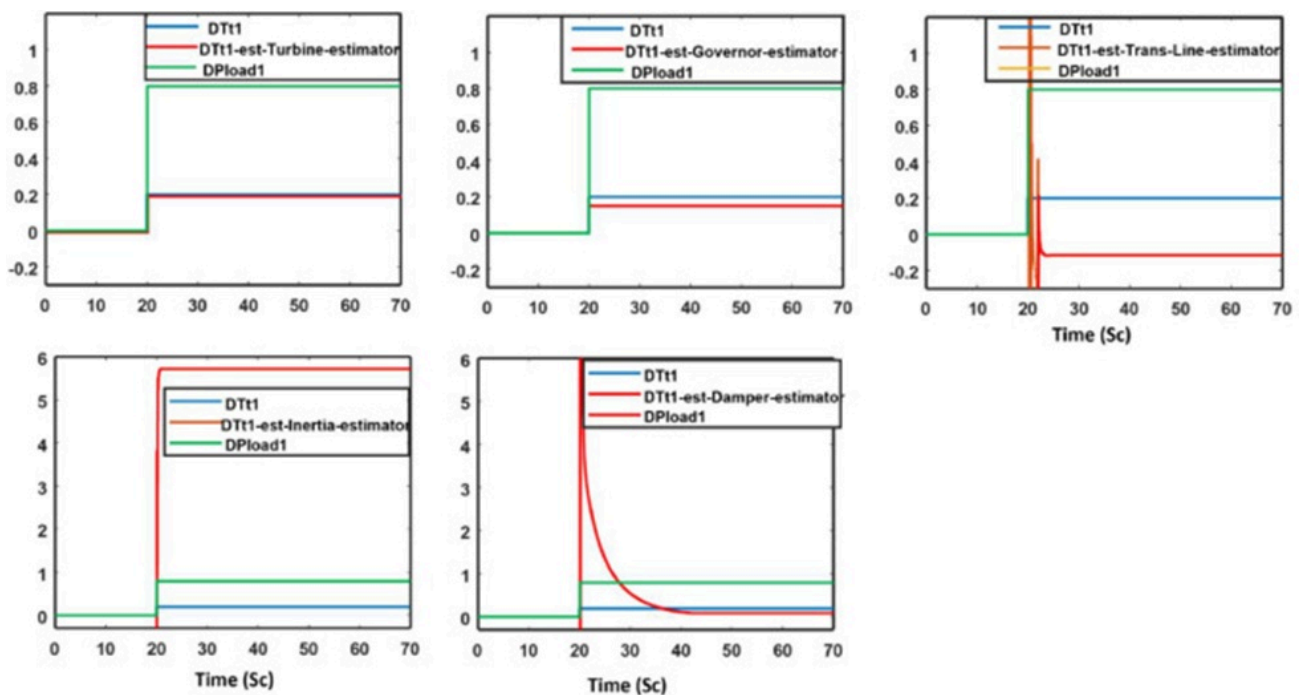


Figure 7. Response of the five estimators to a turbine fault.

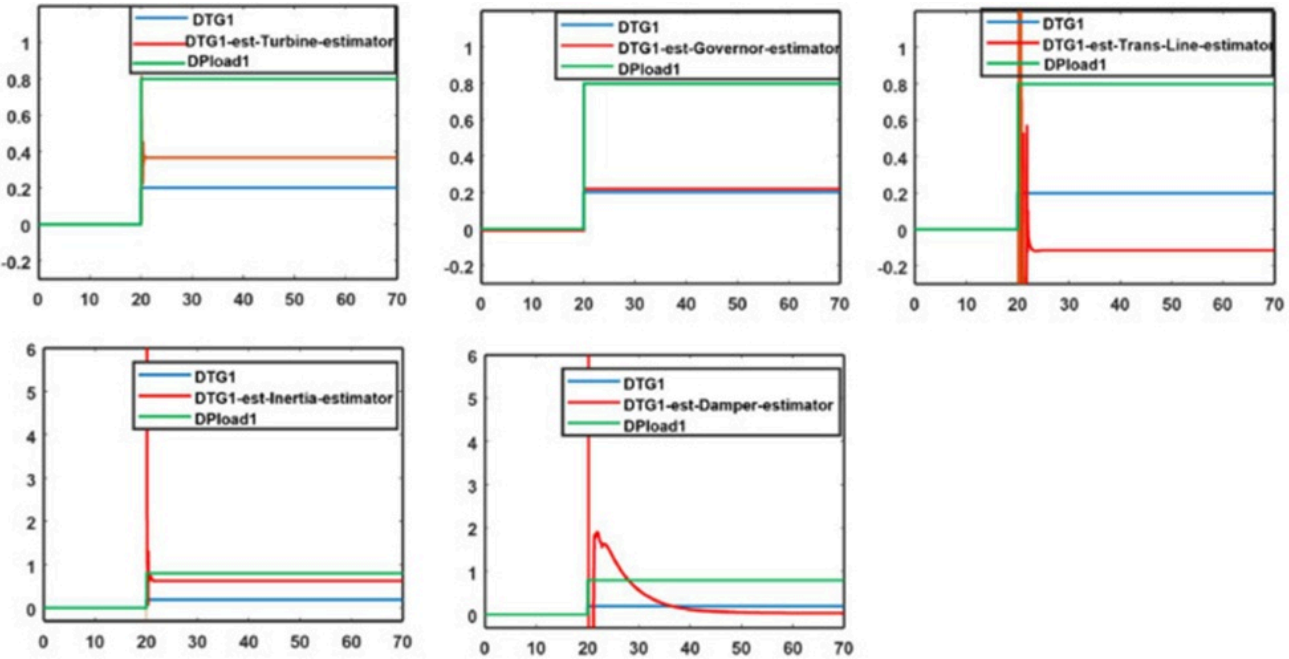


Figure 8. Response of the five estimators to a Governor fault.

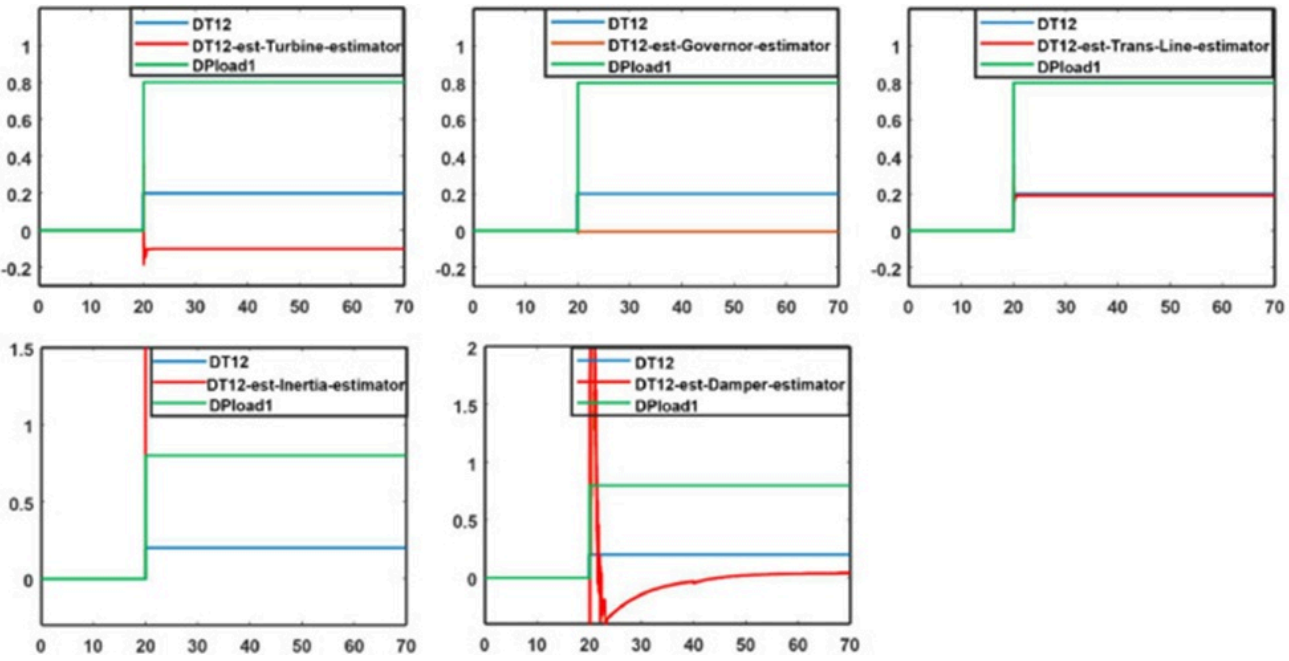


Figure 9. Response of the five estimators to a transmission fault.

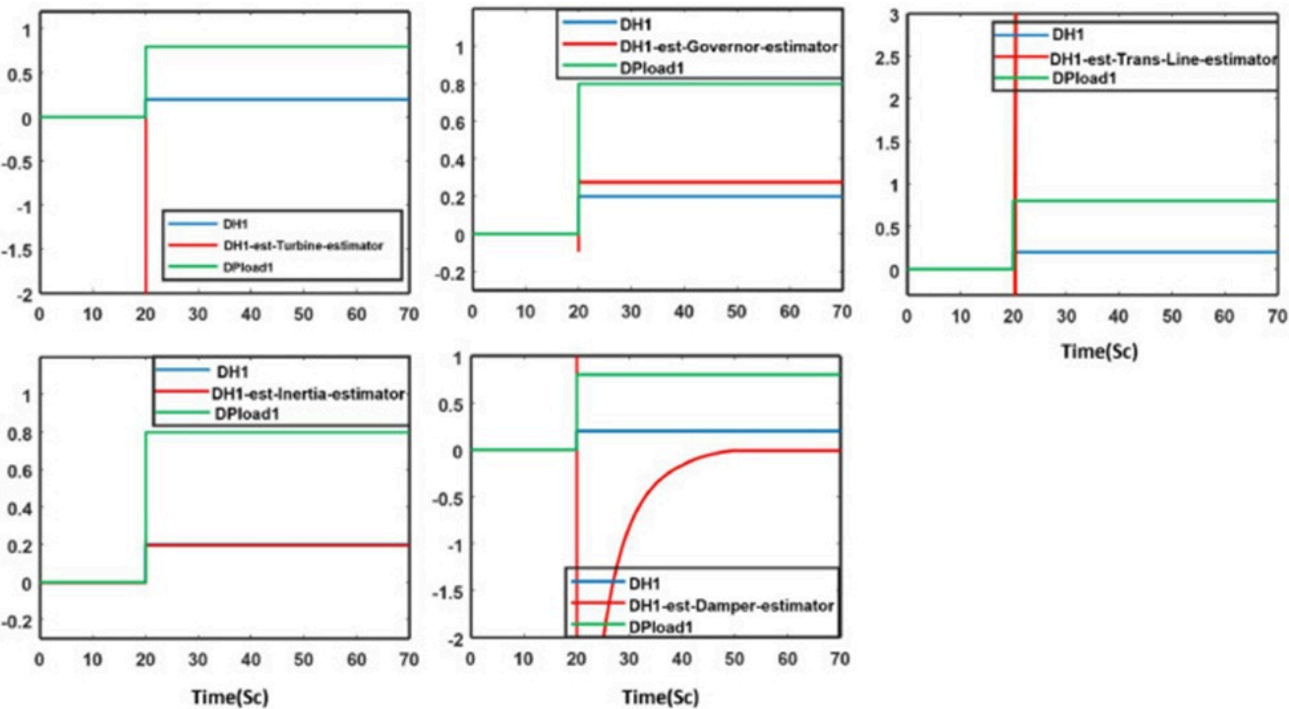


Figure 10. Response of the five estimators to an Inertia fault.

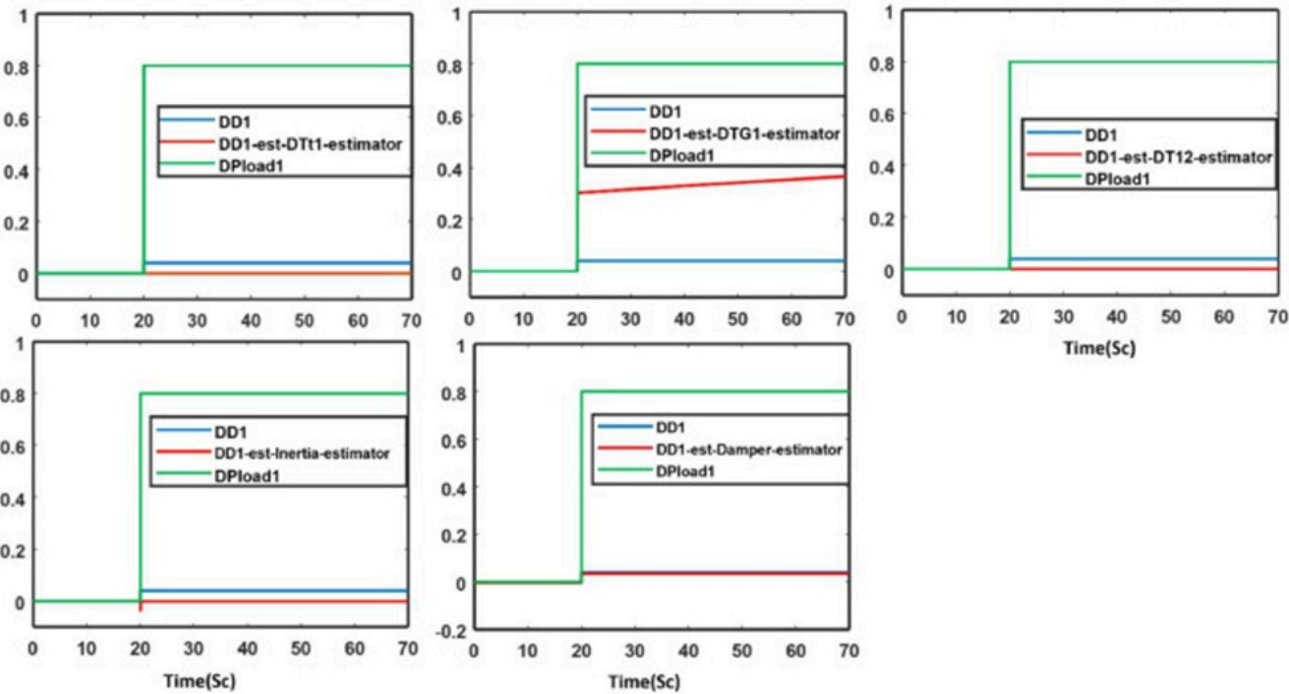


Figure 11. Response of the five estimators to a Damper fault.

An overview of performance across all cases is presented in a single summary table (Table 1).

Table 1. Responses of the five estimators to five different faults.

Fault condition	Turbine parameter estimator	Governor parameter estimator	Transmission line parameter estimator	Inertia parameter estimator	Damper parameter estimator
Turbine fault ($\Delta T_t = 0.2$)	✓	0.4	Oscillatory behavior, settling toward 0^-	$-\infty$	0
Governor fault ($\Delta T_G = 0.2$)	1^-	✓	Oscillatory response, converging to 0^-	Oscillatory response, stabilizing at 0.3	0.3
Transmission line fault ($\Delta T_{t12} = 0.2$)	Oscillatory behavior, converging to -0.2	Oscillatory behavior, converging to -0.2	✓	∞	0
Inertia fault ($\Delta H_1 = 0.2$)	∞	0.7	∞	✓	0
Damper fault ($\Delta D_1 = 0.04$)	Oscillatory response, settling at 0	Oscillatory response, converging to 0^-	Oscillatory response, settling at 0	Oscillatory response, converging to 0^-	✓

✓ : denotes that the estimated value falls inside the acceptable tolerance band.

Overall, all estimators recovered the correct fault magnitude. Regarding fault isolation performance, the following observations stand out:

The inertia estimator uniquely identifies the turbine fault by returning a parameter value of $-\infty$, which serves as a distinctive marker exclusive to this fault type. The same estimator also distinguishes the transmission line fault, as it alone produces a $+\infty$ value in that specific scenario.

Conversely, the turbine estimator and the transmission line estimator can each isolate an inertia fault, since only those two return an infinite magnitude exclusively when an inertia fault is present.

In the presence of a damper fault, all five observers exhibit sustained oscillations that eventually decay to zero. Nevertheless, solely the dedicated damper estimator converges to the accurate (non-zero) parameter value.

Finally, the governor fault partially overlaps with the turbine fault, as acceptable estimates are obtained from both the governor and turbine estimators in those cases. However, a clear distinction is possible thanks to the inertia estimator: it yields an infinite value only for the turbine fault, whereas it remains within the acceptable range for the governor fault. This difference enables reliable separation between governor and turbine faults.

Computational complexity and real-time feasibility

The computational demand of the proposed fault detection and isolation (FDI) scheme represents a key consideration for its real-world implementation. The method comprises an offline design stage and an online operational stage, both of which exhibit polynomial-time complexity, thereby supporting scalability to practical systems.

The offline design of the Mixed H_∞ /Pole Placement observer requires solving a collection of Linear Matrix Inequalities (LMIs). This constitutes a single, one-time computational expense with approximate complexity $O(n^3.5)$, where n denotes the system order (number of states). Such computation remains tractable even for high-dimensional power system models when performed on contemporary engineering workstations.

During online execution—which must satisfy real-time constraints—the observer state update incurs $O(n^2)$ complexity per sampling instant, while each parameter estimator in the bank requires only $O(1)$ operations. Given the limited and fixed number of estimated parameters, the overall online complexity reduces to $O(n^2)$. This level of efficiency renders the scheme well-suited for deployment on modern industrial control hardware, including systems with state dimensions in the hundreds.

This complexity profile offers clear advantages over alternative approaches:

In contrast to deep learning techniques, the proposed model-based strategy avoids the need for prolonged, non-convex training on large datasets. It delivers superior interpretability together with formal robustness and performance guarantees.

To achieve still greater computational efficiency, future investigations will examine model order reduction (MOR) strategies applicable to both the offline and online phases of H_∞ synthesis. A promising candidate is balanced truncation guided by Hankel singular values (HSVs). This technique guarantees a rigorous H_∞ -norm error bound, ensuring that the approximation error between the original and reduced models does not exceed twice the sum of the neglected HSVs. Consequently, the method supports reliable reduction of the state dimension from n to a much smaller value, thereby lowering the offline LMI-solving cost from $O(n^{3.5})$ while preserving verifiable performance bounds. Furthermore, HSV-based balanced truncation can be applied directly to the resulting observer, eliminating states of minor dynamical significance and yielding additional gains in real-time performance without degrading the effectiveness of fault detection and isolation (FDI).

Conclusion

The present work demonstrates the capability to detect and isolate five distinct faults in an interconnected power system using an improved H_∞ observer incorporating pole-placement constraints. The addition of these constraints markedly accelerated the observer's convergence behavior across a range of initial conditions. The developed approach reliably recovered critical dynamic parameters—such as turbine and governor time constants, transmission line parameters, inertia constants, and damping coefficients—each fault type producing a unique identifiable signature.

A central insight of this study is the importance of continuous, real-time monitoring of these parameters, as deviations directly affect both system stability margins and the reliability of fault diagnosis. Such monitoring not only supports prompt and accurate fault detection and isolation but also enables operators to implement corrective measures swiftly, thereby reducing the adverse effects of faults on overall system behavior. Ultimately, this capability strengthens the robustness, resilience, and operational dependability of large-scale interconnected power networks.

The current formulation assumes a constant network topology throughout the fault detection and parameter estimation processes. Although this fixed-topology assumption is standard in many observer-based FDI investigations, it does not capture the full complexity of actual grid operation, where topology may vary due to switching events, line disconnections, load changes, or operational rescheduling. While the H_∞ design inherently provides robustness to parametric uncertainties and shifts in operating conditions, substantial topological alterations could compromise the scheme's precision. Accordingly, future extensions will aim to develop adaptive or gain-scheduled observer structures capable of handling diverse topology configurations, along with mechanisms for online model updating, to maintain dependable FDI performance amid evolving network structures.

This study provides a foundation for several critical research pathways:

- **Robustness to Time-Delays:** Investigate the impact of communication and sensor delays on fault detection accuracy to ensure algorithmic performance in practical, networked implementations.

- **Integration of Renewable Energy Systems:** Extend the FDI framework to accommodate power systems with high penetration of inverter-based resources (e.g., wind and solar), accounting for new fault dynamics introduced by intermittent generation and power electronics.
- **Experimental Validation:** Conduct hardware-in-the-loop (HIL) testing to evaluate the method's scalability, computational performance, and deployment readiness using real-time simulations and physical prototypes.
- **Computational Efficiency:** Apply model order reduction techniques, such as balanced truncation based on Hankel singular values, to reduce the observer's computational complexity for real-time application in large-scale systems.
- **Probabilistic Fault Detection:** Replace fixed thresholds with adaptive, probabilistic strategies (e.g., χ^2 tests) to establish a tunable false alarm rate and enhance robustness under uncertain operating conditions.
- **Grid topology changes:** Extending the framework toward adaptive or gain-scheduled observer banks that can account for multiple topology scenarios, as well as integrating online model adaptation techniques to ensure reliable FDI performance under dynamic network reconfigurations.

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Conflict of interest

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